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Heavy Duty Vehicle Futures Analysis

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Abstract

This report describes work performed for an Early Career Research and Development project. This project developed a heavy-duty vehicle (HDV) sector model to assess the factors influencing alternative fuel and efficiency technology adoption. This model builds on a Sandia light duty vehicle sector model and provides a platform for assessing potential impacts of technological advancements developed at the Combustion Research Facility.

Alternative fuel and technology adoption modeling is typically developed around a small set of scenarios. This HDV sector model segments the HDV sector and parameterizes input values, such as fuel prices, efficiencies, and vehicle costs. This parameterization enables sensitivity and trade space analyses to identify the inputs that are most associated with outputs of interest, such as diesel consumption and greenhouse gas emissions. Thus this analysis tool enables identification of the most significant HDV sector drivers that can be used to support energy security and climate change goals.

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NOMENCLATURE

AEO	Annual Energy Outlook
CI	Compression Ignition
CNG	Compressed Natural Gas
DGE	Diesel Gallon Equivalent
DOE	Department of Energy
ECRD	Early Career Research and Development
EIA	Energy Information Administration
EPA	Environmental Protection Agency
FAF	Freight Analysis Framework
FHWA	Federal Highway Administration
GHG	Greenhouse Gas
GVW	Gross Vehicle Weight
HDV	Heavy-duty Vehicle
ICE	Internal Combustion Engine
kg	Kilogram
LDV	Light-duty Vehicle
LNG	Liquefied Natural Gas
NG	Natural Gas
NGV	Natural Gas Vehicle
NHTSA	National Highway Traffic Safety Administration
NPC	National Petroleum Council
SNL	Sandia National Laboratories
ST	SuperTruck (high efficiency vehicle)
U.S.	United States
VRI	Vehicle Refueling Index

1 INTRODUCTION

This report describes work performed for the Heavy-Duty Vehicle (HDV) and Infrastructure Futures Early Career Research and Development (ECRD) project. This project builds on a model previously developed to characterize light duty vehicle transitions to alternative fuels as part of the Transportation Energy Pathways Laboratory Directed Research and Development project. The ECRD work developed an HDV module for the model to assess the drivers and potential impacts of alternative fuels and energy efficiency technologies in the HDV sector and provide a more expansive view of the on-road transportation energy use future.

In the U.S., HDVs account for 12.4 percent of total petroleum consumption [1] and transport 70 percent of freight by tonnage [2], a number anticipated to continue to grow in the future. Accordingly, the efficiency and types of fuels used by HDVs are of increasing interest as the U.S. addresses climate stabilization and energy independence issues. Current federal efforts related to HDV efficiency include supporting technology development and commercialization as well as issuing regulatory standards. In support of technology development and commercialization for HDVs, the DOE supports the 21st Century Truck public-private partnership, which has accelerated the pace of development and commercialization of HDV efficiency improvements [5, 6], and funds the SuperTruck program, which has made substantial progress toward demonstrating a 50 percent more freight efficient (measured in ton-miles per gallon) Class 8 tractor-trailer [7].

New Environmental Protection Agency (EPA) and National Highway Traffic Safety Administration (NHTSA) sponsored HDV fuel efficiency and greenhouse gas (GHG) emissions standards [3] went into effect for the first time for model year 2014 HDVs and in February 2014, additional Presidential direction was issued to the EPA and the Department of Transportation to establish follow-on regulations by March 2016 [4]. While fuel economy standards have been in place for light duty vehicles (LDVs) since the 1970s, the diversity in construction, use, and ownership of HDVs has made it difficult to institute similar regulations for this segment of vehicles. Despite these difficulties, EPA and NHTSA GHG emissions and fuel consumption regulations went into effect for the first time in 2014. Due to the short time horizon of the first round of regulations, the respective joint regulatory impact analysis [8] focused on technologies that would be widely available in 2014 to reduce tailpipe emissions but did not consider more advanced efficiency technologies, such as hybridization, or alternative fuel conversion in setting the limits defined in the initial four years of regulation.

Interest in reducing GHG emissions and fuel consumption in HDVs has also occurred at the state level. Prior to the enactment of federal fuel economy standards, the California Air Resources Board instituted regulations for tractor-trailers operating in California. These regulations require SmartWay certification for new sleeper-cab tractors as well as adoption of SmartWay certified technologies for both tractors and trailers [9]. U.S. EPA SmartWay certification indicates that the technology has been tested and verified to reduce fuel consumption and lower emissions.

In the longer term, the emergence of these advanced energy efficiency technologies, hybridization, and alternative fuel powertrains for the HDV sector provides significant opportunities for enabling economic-driven HDV sector growth while meeting fuel consumption and GHG emission reduction goals. Several efforts, in addition to the SmartWay initiative, have been made to characterize the effectiveness of individual, and combinations of, efficiency technologies for various categories of vehicles through laboratory testing or modeling and technology roadmap development [10-17]. Considering individual technologies in the context of specific use cases is critical due to the diversity of HDV truck types and operational patterns, which cause a wide range in predicted effectiveness for different technologies with different vehicles. For example, hybridization of a line-haul truck may yield only a 6 to 10 percent reduction in fuel consumption while hybrid trucks used in non-line-haul applications may achieve a 30 to 40 percent reduction in fuel consumption [11]. Conversely, aerodynamics improvements may yield fuel consumption reductions of up to 11.5 percent in line-haul trucks but less than 2 percent in non-line-haul applications [11]. Due to the large number of technology options and respective estimates of efficiency improvement, this model considers notional aggregated technology packages for the different vehicle use cases.

In addition to efficiency technologies, aspects particular to HDV ownership and operational modes can favor the adoption of alternative fuels [18, 19]. Large fleet ownership enables the construction of onsite fueling infrastructure and the predictable and consistent usage patterns of some vocational vehicles and nationwide freight trucks limits the number of public alternative fuel stations necessary to support these vehicles. Well-informed commercial consumers are also prepared to recognize and capitalize on the financial opportunities presented by low cost fuels. The high mileage of line-haul vehicles enables owners of these vehicles to recoup any initial capital outlay relatively quickly from a fuel price differential.

The potential for specific technology or alternative fuel options to impact the emissions and petroleum consumption of the HDV sector will be determined by the rate at which they are adopted over time, based on regulatory requirements and financial incentives. Studies have investigated potential market penetration of these technologies through the use of scenarios considering this adoption over time [13, 20, 21] , estimates of the financial attractiveness of specific technologies [15, 16, 22], or consideration of specific incentives necessary for technologies to be developed and deployed commercially [14]. These studies present limited sets of possible futures but do not consider sensitivities to policy, technology, or economic conditions, which are highly uncertain and can significantly influence results, nor do they assess trade-offs in outcomes. Further, while numerous models have been developed to assess the long term fuel consumption and emissions trajectory of the LDV sector, due to the complexity of characterizing the HDV sector and the relatively limited data availability, few models have considered the HDV sector in detail.

This study develops a detailed HDV fleet model to investigate the factors driving fleet adoption of efficiency technologies and alternative fuel vehicles to provide insight into the inhibitors and drivers toward reduced petroleum consumption and emissions in the HDV sector. Inputs are parameterized to evaluate sensitivity to uncertainties and to determine thresholds impacting the rate of adoption and the potential long term impact of these technologies and alternative fuels.

2 MODEL DESCRIPTION

The model tracks the evolution of heavy-duty vehicle stock in the U.S., its fuel usage, and corresponding demand for raw energy stocks. A diagram of the model is shown in Figure 1 and is based on a similar implementation for light-duty vehicles described in Barter et al. [23]. As diagrammed in Figure 1, the model has three sub-components: a vehicle sub-model, a fuel production sub-model, and an energy supply sub-model. The sub-models exchange price and demand information for the energy supply stocks and fuels considered. The model uses system dynamics concepts (i.e. stocks, flows and feedback loops) to track the changes in various quantities over time and the interactions between variables. No predetermined market share targets are assumed, thus technologies compete directly in the marketplace. The model is implemented as a set of interacting algebraic and differential equations using Python and the Numpy library. Solutions are generated using a third-order Runge-Kutta algorithm with fixed step size.

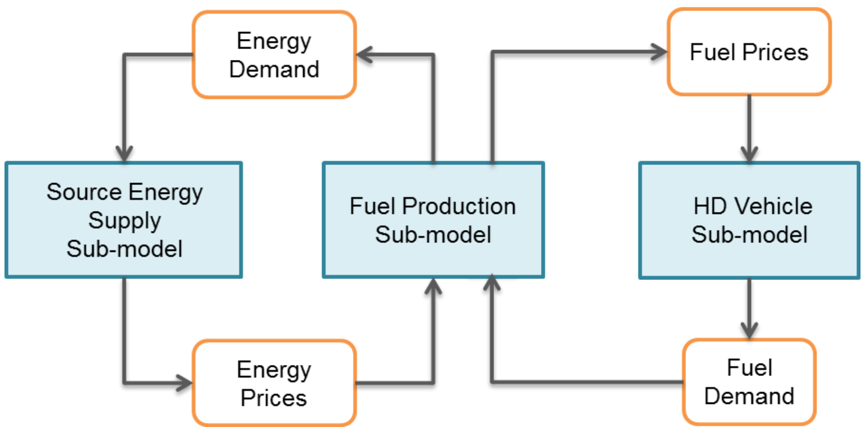

Figure 1: High-level model structure

2.1 Model scope

Gross Vehicle Weight (GVW) Class 7 and 8 vehicles are the second largest consumers of transportation fuel, consuming 17 percent of U.S. transportation petroleum in 2011 (12 percent of total U.S. petroleum use) [1]. As shown in Figure 2, medium-duty vehicles (GVW Class 4-6) consume a comparatively small fraction of fuel nationally. The model therefore focuses exclusively on GVW class 7 and 8 heavy-duty vehicles in the U.S.

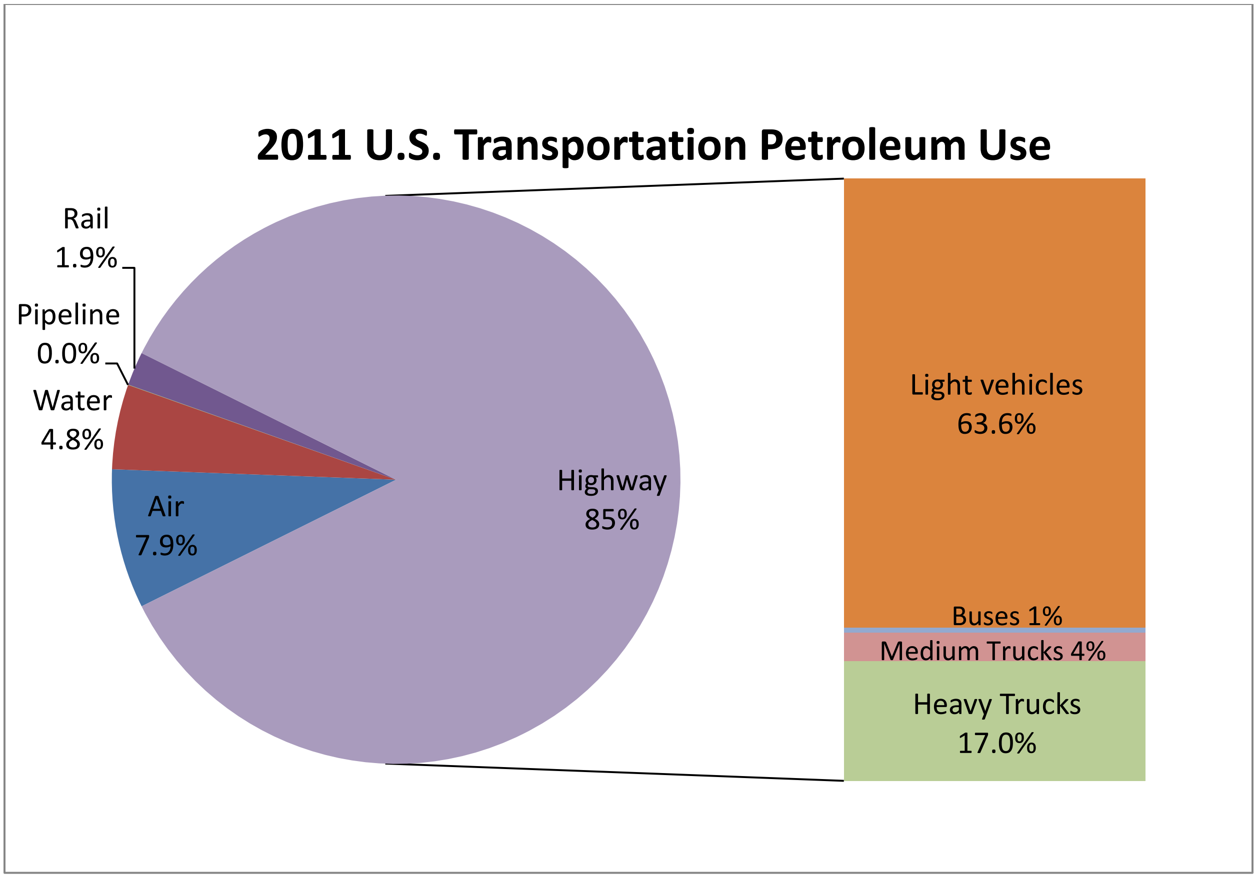

Figure 2: 2011 U.S. Transportation Petroleum Use [1]

To further focus the analysis on the largest and most petroleum-consuming segments of private trucks in the heavy-duty vehicle sector, the following segments of class 7-8 vehicles were excluded:

- Publicly owned vehicles whose adoption is often politically motivated and/or based on individualized circumstances (3.2 percent of GVW class 7 and 8 total petroleum consumption) [24]
- Buses which are largely publicly owned and have already undergone a dramatic adoption of natural gas (0.7 percent of U.S. transportation petroleum, not included in the GVW class 7 and 8 total above [25])
- Emergency vehicles which have very specific operating conditions and purchasing considerations (0.5 percent of GVW class 7 and 8 total petroleum consumption) [24]
- Recreational vehicles which have unique operating conditions and purchasing considerations
- Short-term rental vehicles for which the permanent owner is different from the user (6.4 percent of GVW class 7 and 8 total petroleum consumption) [24]
- Off road vehicles, construction equipment, and farm equipment which are separately regulated and have unique operating conditions

The model currently considers only natural gas as an alternative fuel due to the availability of suitable engines and industry interest in natural gas as a fuel for commercial fleets. Compressed natural gas (CNG) and liquefied natural gas (LNG) are considered separately due to their applicability to different vehicles and uses. LNG has a high-energy density that is well suited for long-distance travel, but it also requires expensive liquefaction and handling infrastructure, and boil-off gas losses may reduce overall efficiency. CNG requires relatively less expensive compressors that can be easily installed onsite, but it has comparatively lower energy density and requires longer refueling times. Hybrid powertrains, both electric and hydraulic, are also available. Hybrid powertrains are considered as separate powertrains in the model due to particular interest in the market potential of hybridization in the HDV sector. Other alternative powertrains, such as biodiesel, electric, and hydrogen fuel-cell, are not currently included. While biodiesel can be mixed with diesel in small proportions (such as B20, a mix of 20 percent biodiesel to 80 percent diesel), using biodiesel exclusively requires engine modifications that are not forthcoming from manufacturers. Similarly, hydrogen fuel cell vehicles are technically feasible, but these vehicles have no widespread commercially availability or refueling infrastructure. Finally, electric vehicles do not currently scale well to heavy-duty applications due to the tradeoff between battery capacity and freight capacity.

The model captures efficiency improvement technology performance and cost impacts in aggregate. This approach is motivated by the variety and number of technologies available and the wide ranges of estimates of their effectiveness under various operating conditions. Example technologies include aerodynamic improvements, wide-based single tires, low-viscosity lubricants, automatic tire inflation, idle reduction technologies, and weight reduction. Considering aggregations of technologies allows parameterization across the cost and performance trade spaces to provide insight on thresholds to achieve market success that are generally applicable to all technologies.

Changes in vehicle operation procedures can also improve the energy efficiency of HDVs. These changes could include improving logistics, shifting goods transport to more efficient transportation modes, using longer combination vehicles, speed limiting, and other forms of driver behavior modification. These changes are not considered in the model because of their interactions with safety and logistical constraints, which are difficult to capture, as well as the intended technology focus of this analysis.

Sections 2.2 and 2.3 describe the model implementation in detail. Several assumptions were made to focus the design of the model to match the purposes of the analysis. Significant model assumptions that are not otherwise discussed in the text include the following:

- A load specific fuel consumption metric is used (fuel consumption per ton-mile) in accordance with recommendations made by the National Academy of Sciences [11]. This metric differs from the miles per gallon metric commonly used for light-duty vehicles and reflects the load-carrying purpose of HDVs.
- The growth in ton-miles of on-road freight per year is exogenous to the model and therefore intermodal shifting of freight traffic in response to fuel or vehicle price (i.e., rebound effect) is not considered.
- Aggregated sets of efficiency technology improvements are assumed to provide the same percentage fuel consumption reduction per ton-mile across powertrains.
- The model does not consider efficiency improvements designed exclusively for on-board vocational equipment, such as cement mixing or refuse truck hydraulics.

- Although the interest in alternative fuel trucks in the resale market may be a significant decision factor for some new vehicle purchases, the resale market is not modeled. However, the movement of trucks across segments as they age is modeled.
- After-market powertrain conversions not completed at the time of initial purchase are not considered.
- Although tractors are often not consistently paired with dedicated trailers, for the purposes of the model combination tractor-trailers are considered as joined units.
- Vehicle maintenance costs are not considered in the model due to a lack of available data on the cost and frequency of maintenance required for the various powertrains and vehicles.

2.2 Vehicle Stock Modeling

2.2.1 Vehicle Segmentation

The model starts in 2012 with 3.38 million Class 7 and 8 heavy-duty vehicles in service in the United States that fall within our bounding assumptions described above. The initial truck stock is developed from Polk vehicle registration data [24] and segmented by the seven dimensions listed in Table 1.

Table 1: Vehicle Attributes

Attribute	Segments	Subscript Notation
Age	0-17+ years	*a*
State	48 continental U.S. states and the District of Columbia	*r*
GVW Class	Class 7 Class 8	*g*
Body Type	Single Unit Truck Combination Tractor-Trailer	*b*
Powertrain	Diesel Compression Ignition (CI) Diesel Hybrid- electric or hydraulic (CIHYBRID) Diesel High Efficiency (CIST) Diesel High Efficiency Hybrid (CIHYBRIDST) Compressed Natural Gas Spark Ignition (CNG) CNG Hybrid- electric or hydraulic (CNGHYBRID) CNG High Efficiency (CNGST) Liquefied Natural Gas (LNG) LNG High Efficiency (LNGST)	*n*
Fleet Size	≤10 trucks, ≤100 trucks, ≤1000 trucks, and >1000 trucks	*s*
Refueling station type	Interstate truck stops Local gas stations Private	*t*

The vehicle stock, **V**, can therefore be written as,

$$\boldsymbol{V} = \boldsymbol{V}_{argbnst} \quad .$$

Heavy-duty truck stock growth is assumed to scale with expected growth in on-road freight, which is derived from the Freight Analysis Framework (FAF) model [26]. Specifically, the percentage growth in total on-road truck ton-miles, as predicted by the FAF model, is the percentage growth in truck stock for the same year. Thus the ton-mile allocation per truck is constant over time within each segment and all segments, except for powertrain, grow uniformly. The constant values of ton-miles per truck are derived from the Vehicle Inventory and Use Survey (VIUS) 2002 survey database [27] based on age, GVW, body type, and refueling station type ($\mathbf{M} = \mathbf{M}_{agbt}$). Survival probability curves used by the EPA for recent efficiency standard rule making [15] are used to develop truck scrap rates, which vary over truck age, GVW, and body type ($\mathbf{W} = \mathbf{W}_{agb}$). Scrap rates are also assumed to be constant over time and independent of powertrain. The evolution of each vehicle segment can therefore be written as,

$$\frac{d\boldsymbol{V}_{a=0,rgbnst}}{dt} = \sigma^{V}_{rgbnst}\boldsymbol{S}\sum_{an}\boldsymbol{V}_{argbnst}; \qquad \frac{d\boldsymbol{V}_{argbnst}}{dt} = \boldsymbol{W}_{agb}\boldsymbol{V}_{argbnst},$$

where **S** is the overall sales rate, **W** is the scrap rate, and σ^{v} is the consumer sales fraction by powertrain for each vehicle segment such that, $\Sigma_n \sigma^{v}_{rgbnst} = 1$. The sales rate is obtained from the difference between the overall growth and scrap rates. Prior to computing this difference, vehicles are migrated from some segments to others to capture the used truck market. Essentially, the distribution of age for every fleet size-station type segment is maintained despite uniform growth across all segments. In this way, more new trucks are assigned to certain segments, specifically larger fleets with greater access to capital and higher mileage vehicles that use highway truck stops.

Ton-mile fuel economy for existing trucks on the road and future model years is derived from a variety of data sources. Energy Information Administration (EIA) Annual Energy Outlook (AEO) reports dating back to the 1990s [25] are used to provide efficiency data for existing trucks. New trucks in model years 2014-2017 are assumed to comply with the new NHTSA/EPA regulations [8]. The NHTSA/EPA regulatory impact analysis also provided the template for converting the EIA efficiency data from miles per gallon to ton-miles per gallon. Efficiency data from the National Petroleum Council (NPC) [20] was used for CI, CIHYBRID, and CNG/LNG trucks beyond 2017. This data source was also used to differentiate class 7 and 8 vehicles, as well as combination tractor-trailer versus single unit trucks. The quantitative improvement of the high efficiency powertrain variants used results from a study by TA Engineering, Inc. [7]. The TA Engineering study calculated a 50 percent efficiency improvement at powertrain introduction in 2015 and a 33 percent improvement by 2050, due to technology diffusion into the standard powertrains. These improvement factors were further parameterized in this model. Finally, to account for LNG burn-off from the fuel tanks, LNG trucks using gas stations or private infrastructure (indicating non-continuous operation) were penalized 10 percent in ton-mile efficiency.

2.2.2 Vehicle Purchase Model

The segment sales fractions in each time-step, σ^{v}, are assigned using a logit choice model [28]. The sales fraction for a given segment is determined by,

$$\sigma^{V}_{rgbnst} = \frac{k_n\theta_{rnt}\boldsymbol{U}^{V}_{rgbnst}}{\sum_n k_n\theta_{rnt}\boldsymbol{U}^{V}_{rgbnst}}; \qquad \boldsymbol{U}^{V}_{rgbnst} = \exp\left(-\beta\frac{\boldsymbol{C}^{G}_{rgbnst}}{\left\{\boldsymbol{C}^{G}_{rgbnst}\right\}_n}\right),$$

where $\mathbf{U}^V$ is the utility, β is the logit exponent, $\mathbf{C}^G$ is the total cost, and $\{\bullet\}_n$ is a reference cost taken to be the average cost over all powertrains. The baseline logit exponent value is β = 25, but this is an uncertain parameter that is included in the model sensitivity studies. The utility shares are limited by powertrain availability, *k*, and willingness-to-consider an alternative fuel based on infrastructure availability, θ. The high efficiency variations of the powertrains (ST) are assumed to be the product of the DOE SuperTruck program and available starting in 2015. The willingness-to-consider is a logit curve based on the ratio of alternative fuel stations relative to diesel stations in a given state,

$$\theta_{rnt} = \left[1 + exp\left(-\frac{\phi_{rnt} - \theta_t^0}{\theta^1}\right)\right]^{-1}; \qquad \phi_{rnt} = \frac{\sum_{f\in n} \Phi_{rtf}}{\Phi_{rt,f=diesel}} ,$$

where θ^0 is an input parameter that centers the logit curve (infrastructure willingness factor), θ^1 controls the logit slope, ϕ is the alternative fueling station ratio, Φ is the absolute number of alternative fueling stations, and the subscript *f* refers to the fuel. The default values for the constants are $\theta^0 = 0.1$ and $\theta^1 = 0.02$. Note that θ=1 for vehicles that use private refueling.

The generalized vehicle purchase costs, including penalties, are amortized over a payment period and converted to a per ton-mile cost using the annual ton-miles traveled [29],

$$\boldsymbol{C}_{rgbnst}^G = \boldsymbol{A}_s\left(\frac{\boldsymbol{C}_{gbnt}^V}{\boldsymbol{M}_{a=0,gbt}}; \boldsymbol{L}_s\right) + \boldsymbol{C}_{rgbnst}^F + \frac{\boldsymbol{C}_{gbnt}^P}{\boldsymbol{M}_{a=0,gbt}} ,$$

where $\mathbf{C}^V$ is the vehicle capital cost, $\mathbf{C}^F$ is the fuel cost per ton-mile, $\mathbf{C}^P$ is the penalty costs, **L** is the required payment period, and **M** is the annual ton-miles per truck. The sale of depreciated used trucks is not included in the generalized purchase cost consideration due to lack of available data. The function, $\mathbf{A}_s(\bullet;\mathbf{L})$, amortizes the cost to the buyer over a payment period acceptable to the buyer with no discounting. To capture the differences between small fleet buyers who might have limited access to capital and larger fleet buyers who likely have greater access to capital, the acceptable payment period, **L**, is a function of fleet size,

$$\boldsymbol{L}_s = \begin{cases} L^0, & \text{Fleet size 0-10} \\ L^0 + (L^1 - L^0)/3, & \text{Fleet size 11-100} \\ L^0 + 2(L^1 - L^0)/3, & \text{Fleet size 101-1000} \\ L^1, & \text{Fleet size} >1000 \end{cases}$$

where L^0 and L^1 are user parameters defining the acceptable payment period for the smallest and largest fleets, respectively. Linear interpolation is used for the intermediate fleet sizes. Since this variation of payment period as a surrogate for access to capital is an approximation, these parameters are investigated in the parametric studies.

Similar to vehicle efficiency data, vehicle purchase costs, $\mathbf{C}^V$, are adapted from a few different sources, as no single source provided all the data necessary. The NPC study [20] provided the future costs of CI class 8 combination tractor-trailers, as well as the cost premiums for hybridization and natural gas (both CNG and LNG) powertrains. The hybridization cost premiums however led to unrealistic sales rates and were therefore corrected to match estimates from Gao et al. [16]. For the same reason, natural gas powertrain costs were increased by 10 percent. The high efficiency powertrain variants were assigned costs based on TA Engineering, Inc. [7], which predicted declining purchase premiums over time due to diffusion of the high efficiency technologies. Cost differentiation between class 7 and class 8 vehicles, as well as between combination tractor-trailers and single unit trucks, was derived from Polk data [24]. It was further assumed that tractor-trailers using highway truck stops would use sleeper cabs but otherwise would use day cabs.

Penalty costs, $\mathbf{C}^P$, are included to quantify limitations of alternative powertrains in terms of fuel tank range and time spent refueling. This penalty is computed as an annual estimate of the time spent at the pump and is expressed as,

$$\boldsymbol{C}^P_{gbnt} = \delta^P \sum_f \frac{\boldsymbol{M}_{a=0,gbt}\Xi_{a=0,gbntf}}{\boldsymbol{H}_{tf}}; \qquad \Xi_{agbntf} = \frac{1}{\eta_{agbntf}}; \qquad \delta^P = \$30/\text{hour};$$

$$\boldsymbol{H}_{tf} = \begin{cases} 10\ \text{gal/min}, & \text{Diesel at a gas station} \\ 60\ \text{gal/min}, & \text{Diesel at a truck stop} \\ 4\ \text{DGE}^1/\text{min}, & \text{CNG public refueling} \\ 45\ \text{DGE/min}, & \text{LNG} \end{cases}$$

where **H** is the refueling rate, Ξ is the fuel consumption per ton-mile, η is the fuel economy, and δ^P monetizes time. The refueling rate values come from pump manufacturer specifications and EPA regulations. The estimation of the penalty is, of course, an approximation and is therefore also included in the parameterization.

The fuel cost per ton-mile, $\mathbf{C}^F$, is the product of the fuel price and the fuel consumption per ton-mile of a vehicle,

$$\boldsymbol{C}^F_{rgbnt} = (1 + q_{nt}) \sum_f \boldsymbol{P}^F_{rtf}\Xi_{a=0,gbntf}$$

where $\mathbf{P}^F$ is the price of fuel, and q is a user-defined multiplier for the operation of private infrastructure. The cost of buying, operating, and maintaining private refueling equipment is appended to the fuel cost. In this way, the cost scales appropriately for large versus small fleets and high versus low ton-mileage vehicles. The default value of q for natural gas vehicles (NGVs) is assumed to be 0.3 [30].

2.2.3 Infrastructure Growth and Total Fuel Demand

The model tracks the number of public refueling stations by region. The ratio of alternative fuel pump stations to alternative fuel vehicles is denoted the Vehicle Refueling Index (VRI) [31] and is a surrogate for infrastructure growth in the model,

$$\frac{d\Phi_{rtf}}{dt} = (\text{VRI}) \sum_{gbs,n\in f} \frac{d\boldsymbol{V}_{a=0,rgbnst}}{dt}$$

The VRI is a policy-driven input parameter that scales with the number of AFVs purchased in a given region to determine the number of new alternative refueling stations added. By parametrically adjusting

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[1] DGE is diesel gallon equivalent.

the VRI, the model can explore the dependency between powertrain adoption and refueling infrastructure growth. Thus, infrastructure investment is not directly captured but is assumed to dynamically respond to sales. U.S. DOE [32] data was used to for the initial refueling station distribution by region and fuel type.

As shown in Figure 1, the vehicle sub-model outputs the total fuel use demand, $\mathbf{D}^F$. This is computed by an accounting of the total ton-mileage covered by the HDV stock and the fuel consumption rate,

$$\boldsymbol{D}_{rf}^{F} = \sum_{agbnst} \boldsymbol{V}_{argbnst} \boldsymbol{M}_{agbt} \Xi_{agbntf}$$

2.3 Fuel Production and Commodity Supply

The fuel production and supply sub-models are qualitatively described here. A mathematical description of their inner workings can be found in Barter et al. [23].

The fuel module calculates the cost and energy source mix of transportation fuels, given fuel demand from the vehicle model and energy source costs from the energy source sub-model. The set of fuels in the model is diesel, CNG, and LNG. Other fuels used in light-duty applications could easily be included in future developments. The fuel demand in each state is matched with the corresponding raw energy feedstocks using conversion efficiencies specified by the GREET model [33]. State-by-state pricing variations are enforced for diesel and natural gas due to the complexities of the supply and refining network for those fuels. Well-to-pump CO_2-equivalent GHG emissions are computed using process estimates from GREET [33]. Pump-to-tailpipe GHG emissions are computed using the CO_2-equivalent content of the fuel and the total fuel demand. The model tracks criteria pollutants in a similar fashion using the same data sources.

The U.S. DOE's AEO reference case was the source for crude oil, coal, and natural gas prices [25]. Crude oil and coal were assumed to be global and national commodities, respectively, with prices unaffected by perturbations in U.S. fuel demand. Natural gas prices varied by region but were similarly assumed to be unaffected by transportation demand.

3 NUMERICAL ANALYSIS

While other HDV models have considered technology roadmaps and necessary adoption rates to meet specific targets and the cost effectiveness of particular technologies, the purpose of this parametric model is to provide insight into the answers to the following questions:

- Considering the perspectives of vehicle purchasers with regard to adopting new technologies and/or alternative fuels, what realistic future targets could be set with respect to reducing HDV petroleum consumption and emissions?
- What alternatives play an essential role in meeting these targets? How do efficiency technologies impact alternative fuel adoption? What is the potential impact of both efficiency technologies and alternative fuels over the next few decades?
- What are the relative tradeoffs between reduction in particulate emissions, GHG emissions, and petroleum consumption?
- What factors or conditions most strongly influence the widespread adoption of efficiency technologies or alternative fuels?
- What attributes of the different vehicle segments most significantly drive or limit widespread adoption of efficiency technologies or alternative fuels? Which options may have significant impact for each vehicle segment?

3.1 Baseline Scenario

The baseline scenario demonstrates the time series computations of the model and shows one possible future progression for the HDV sector. The baseline scenario figures should not be interpreted as an expected future projection, but instead as a reference scenario, seeded with one set of parameter values, to be used for comparison to scenario results using other sets of parameter values. The parametric analysis is discussed in subsequent sections, generally with respect to impact on the projected fleet in year 2050. The time series figures in this section present a sample of the time series calculations behind each year 2050 projection presented in the parametric analysis. The baseline scenario represents the case where no multiplier values are used and the remaining parameters are assigned the following values:

Table 2: Baseline Parameter Values

Parameter		Value
Choice Function Exponent	β	25.0
Station Growth	VRI	0.2
Infrastructure Willingness Factor	Θ^0	0.1
Infrastructure Cost Factor	q	0.3
Payback Period (Large Fleets)	L^1	2.0 years
Payback Period (Small Fleets)	L^0	0.75 years

Figure 3, Figure 4, and Figure 5 show the initial base vehicle costs for new vehicle sales. These costs are predetermined and based on data used in the NPC study [20] and data provided by Polk [24]. For all segments, the standard diesel powertrain is the least expensive powertrain and the high efficiency hybrid diesel powertrain is the most expensive. For early model years hybrid diesel powertrains are less expensive than natural gas powertrains, but by 2020 natural gas powertrains are cheaper than hybrid and high efficiency diesel powertrains for all vehicle segments.

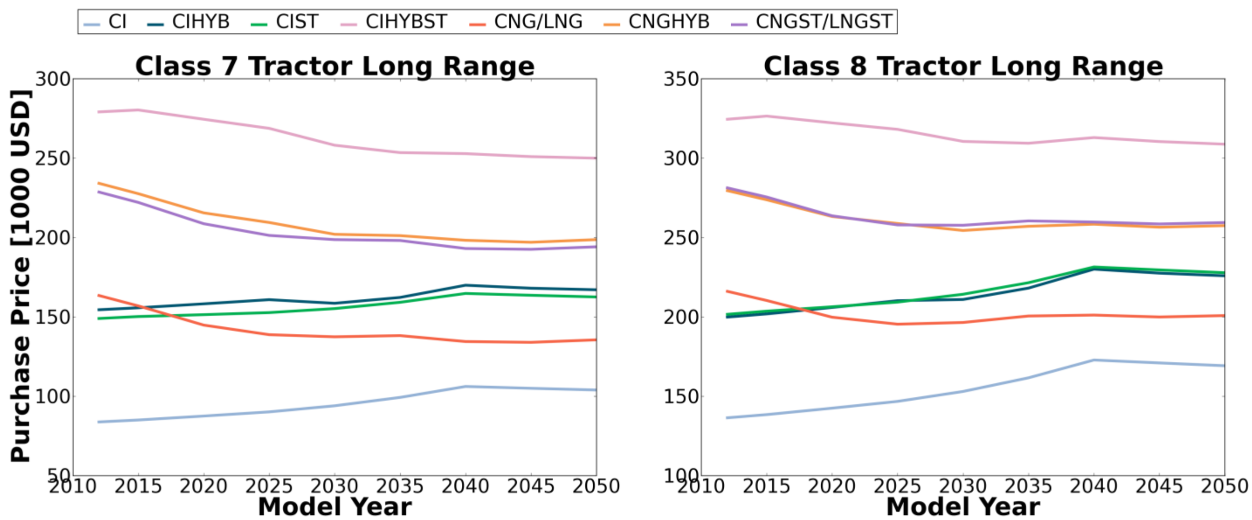


Figure 3: Initial vehicle cost for class 7 and 8 long range (sleeper cab) tractor trailers by model year.

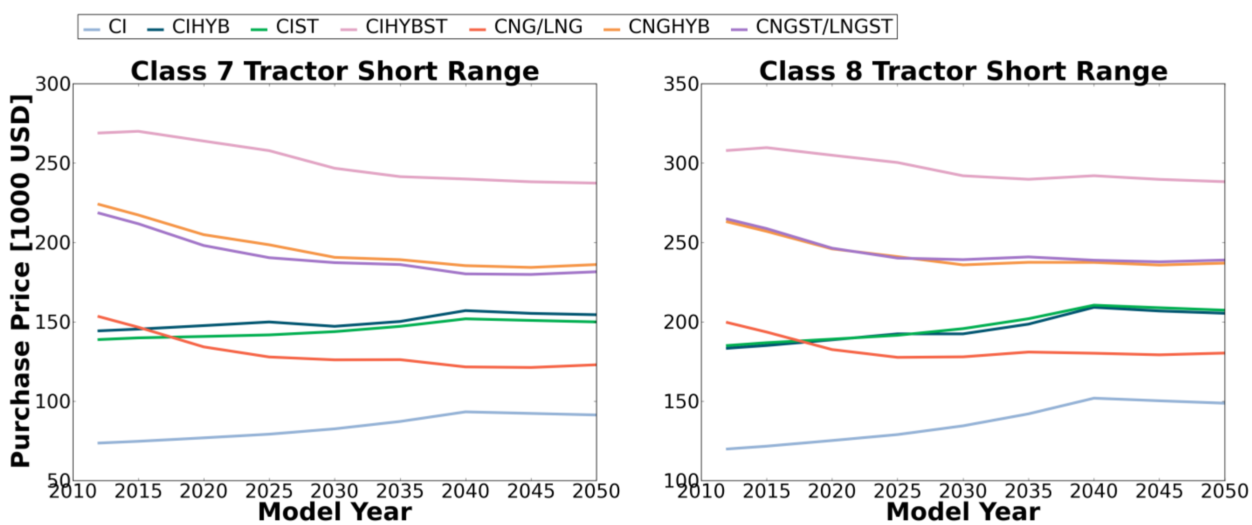


Figure 4: Initial vehicle cost for class 7 and class 8 short range tractor trailers by model year.

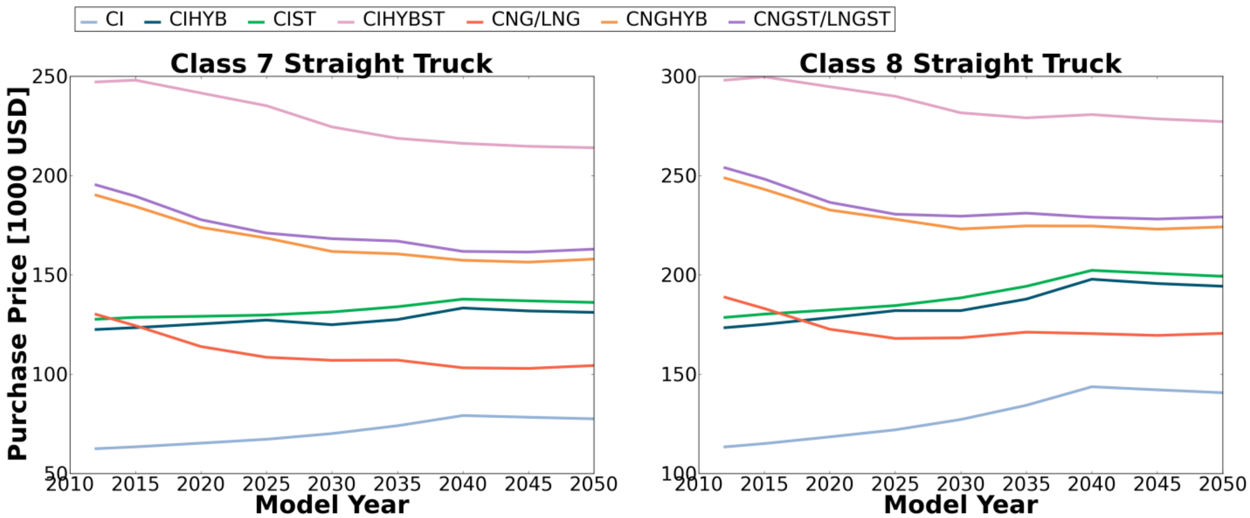


Figure 5: Initial vehicle cost for class 7 and 8 straight trucks by model year.

Figure 6 and Figure 7 show the fuel economy for each powertrain based on model year. These economies are input values and are adapted from studies by the NPC [20] and the National Research Council [11]. LNG and CNG vehicles are assigned the same overall efficiency, but short range LNG vehicles (i.e., those fueling at gas stations or private facilities) are assigned an additional 10 percent penalty to the efficiencies represented in the figures due to burn-off. On a diesel gallon equivalent basis, diesel vehicles are more efficient than the base NGVs but generally less efficient than CNG hybrids and high efficiency vehicles.

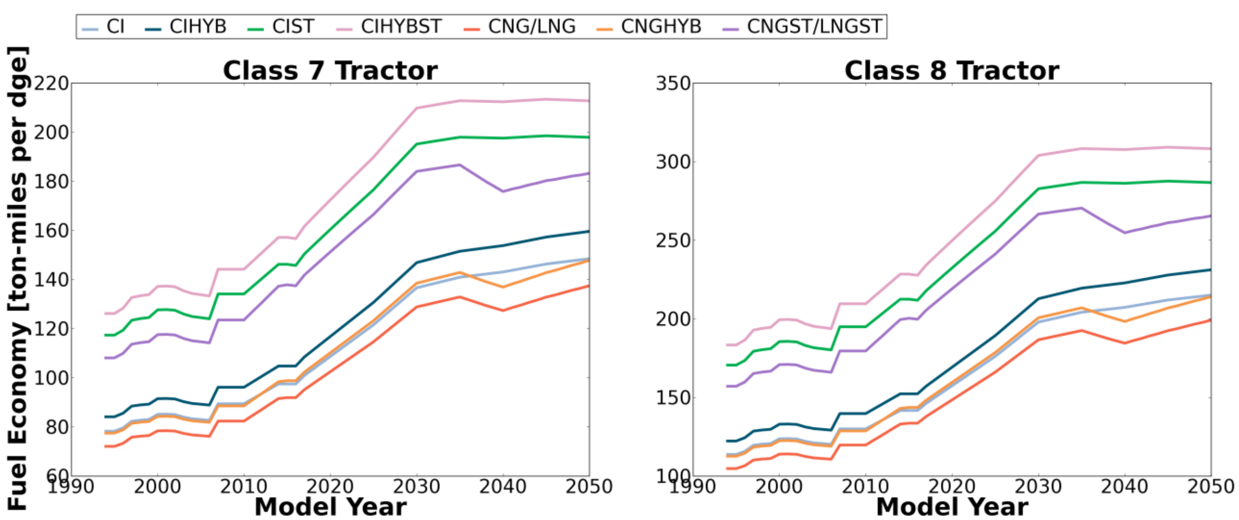


Figure 6: Fuel economy of class 7 and 8 tractor trailers.

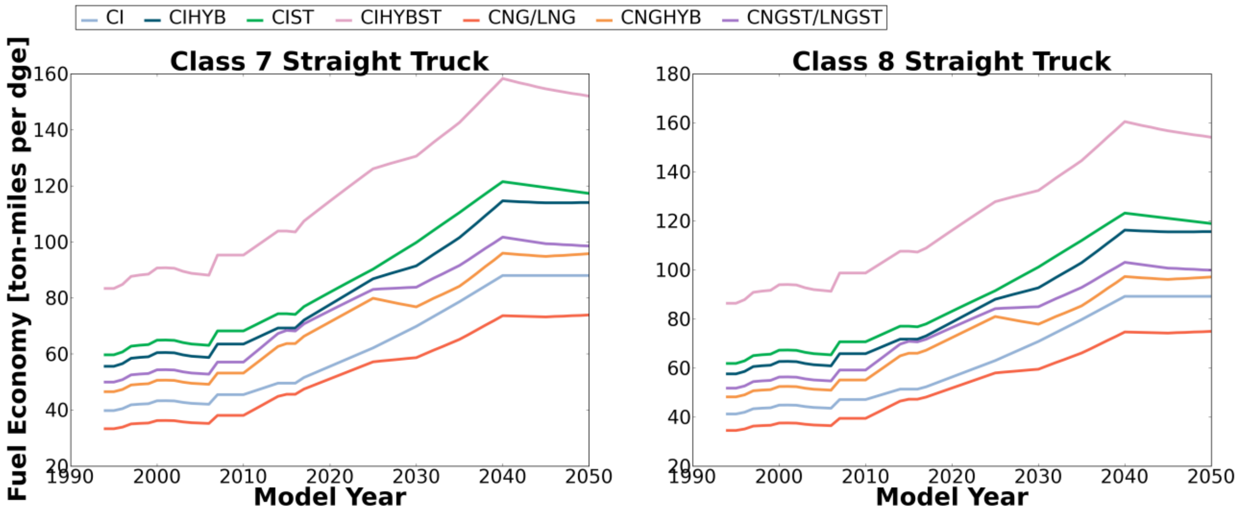


Figure 7: Fuel economy of class 7 and 8 straight trucks.

Figure 8 shows the baseline pump fuel prices over time in diesel gallon equivalents. For this case, natural gas prices remain relatively stable while diesel increases significantly, particularly between 2035 and 2050.

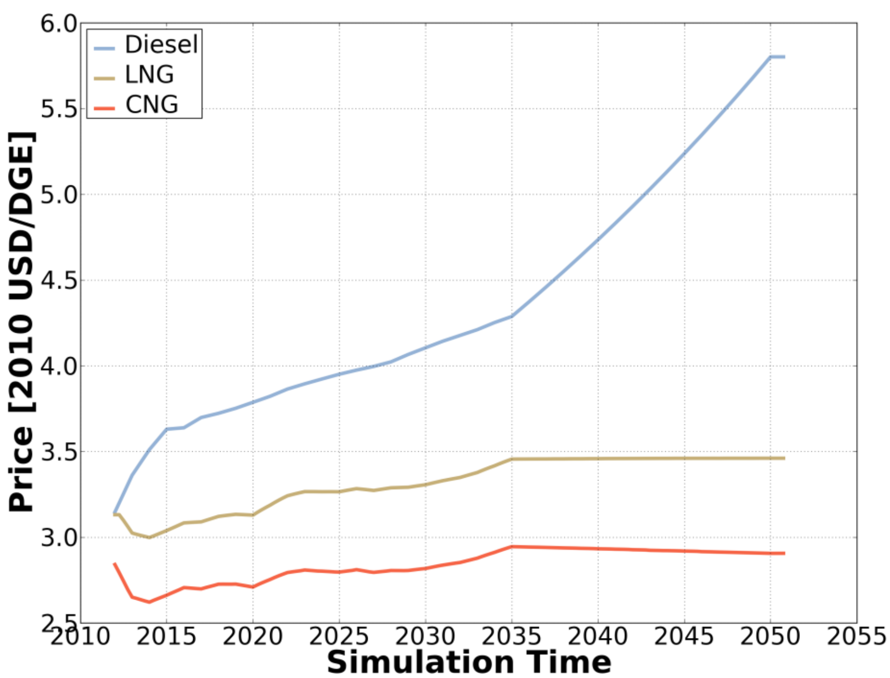


Figure 8: Baseline pump fuel prices over time.

Figure 9 shows powertrain sales and stock over time for the baseline scenario. In the model, high efficiency (SuperTruck) powertrains become available in 2015 and the sales figure shows some initial market for these vehicles. However, as time progresses, sales of high efficiency vehicles are overtaken by NGVs. Particular growth in sales of NG vehicles is seen around 2035 when the diesel fuel price premium begins to increase sharply. With the exception of the high efficiency diesel powertrain, hybrid and high efficiency vehicle sales for all fuel types remain small over the simulation time. For this baseline scenario, standard diesel powertrains remain the substantial majority over the model timeline.

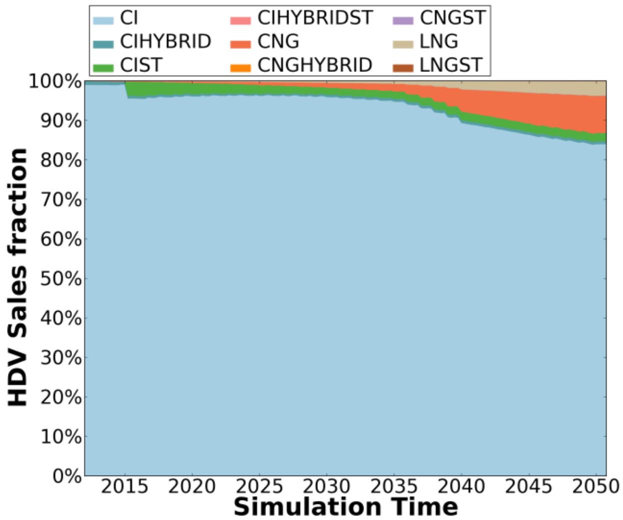


Figure 9: Baseline scenario sales and stock over time.

Figure 10 shows the impact of the sales and fleet demographic shifts over time on reducing GHG emissions. The increasing efficiency of the baseline powertrains over time and the shift toward the use of natural gas contribute to significant GHG emission reductions over time. The GHG emissions per ton-mile decrease over 40 percent over the model timespan. However, due to the growth in the amount of on-road ton-mile transport, the total GHG emissions show a decline around 2035 but an overall growth of over 15 percent over the model timespan.

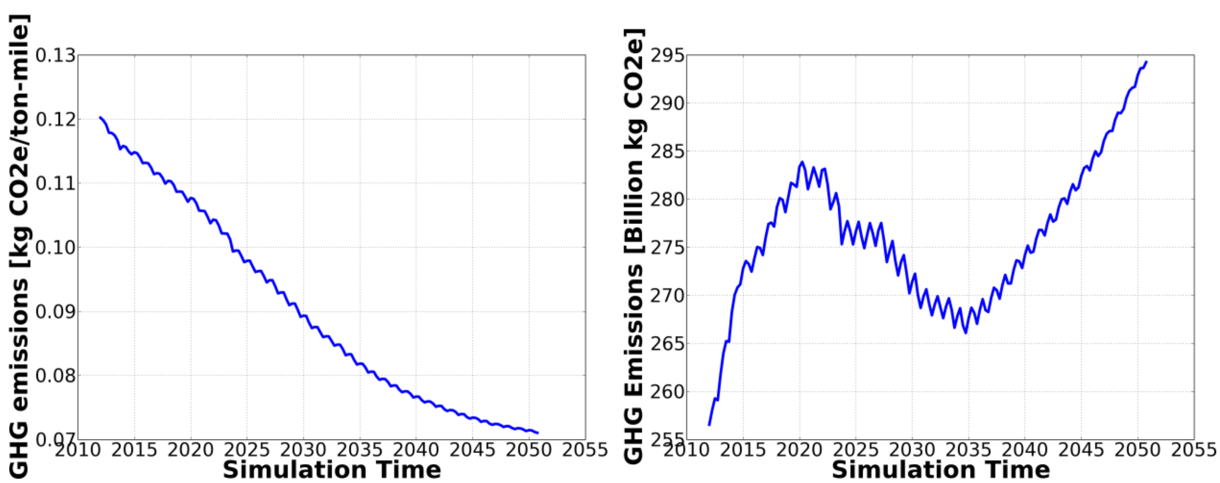
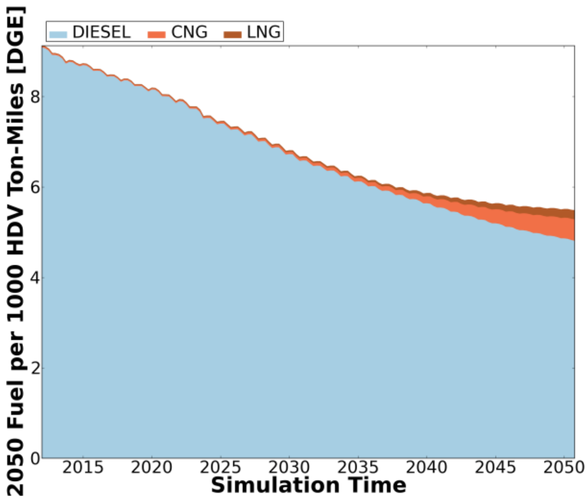


Figure 10: Baseline scenario GHG emissions per ton-mile and total GHG emissions.

Figure 11 shows the impact of the sales and vehicle stock evolution on fuel consumption. The fuel per ton-miles figure shows how the averaged fuel use per ton-mile of transport changes over time. Apparent are both the overall decrease in fuel energy required for each ton-mile of transport as well as the increasing, though relatively small, contribution of natural gas, as both LNG and CNG, in the fuel mix. The total fuel demand figure shows the total HDV fuel demand over time for diesel, LNG, and CNG.

Diesel consumption remains fairly constant between 2015 and 2050 while LNG and CNG consumption grow, particularly after 2035.



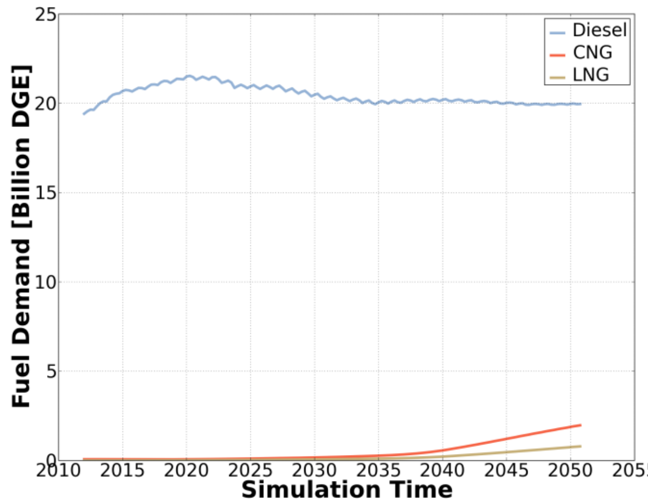


Figure 11: Baseline scenario average fuel composition for each ton-mile of transport and total fuel demand.

Figure 12 shows the growth in fueling stations for each fuel. The rate of growth is most significant for LNG stations due to the small initial number of stations and the growth in demand as the number of LNG vehicles increases. As shown in Figure 13, LNG vehicles typically rely on public infrastructure for refueling whereas CNG vehicles are more reliant on private infrastructure for refueling which explains the relatively high growth in LNG public infrastructure as compared to the minimal growth in CNG infrastructure.

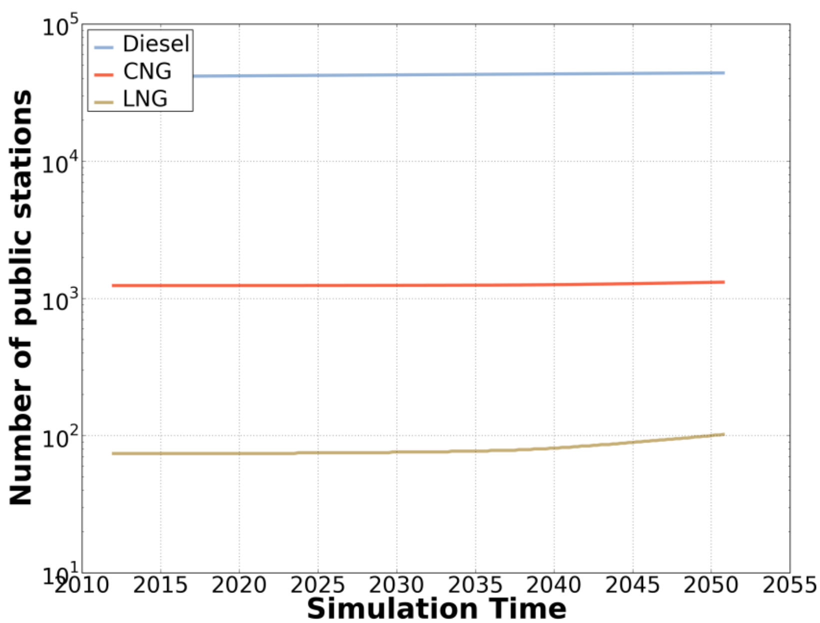


Figure 12: Baseline scenario public infrastructure development over time.

Figure 13 shows the vehicle stock broken out by fueling location. Vehicles refueling at gas stations are local transport vehicles that do not have refueling at their home base. No widespread adoption of alternative fuels or high efficiency technologies occurs in this segment, which may be due to the lower annual fuel costs associated with local vehicle operation that provides less incentive for adopting a less expensive fuel or reducing fuel consumption. The lack of significant alternative fuel adoption in this segment may also be due to the relatively small number of natural gas fueling stations. By contrast, more adoption of high efficiency technologies is shown among vehicles refueling at truck stops, which may be due to the relatively high annual fuel costs associated with long haul vehicles. By 2050 over 10 percent of private refueling vehicles use CNG. With the relatively inexpensive cost of CNG as compared to diesel and the opportunity for overnight refueling to mitigate slow refueling times, CNG may be an attractive option for private fleet refueling.

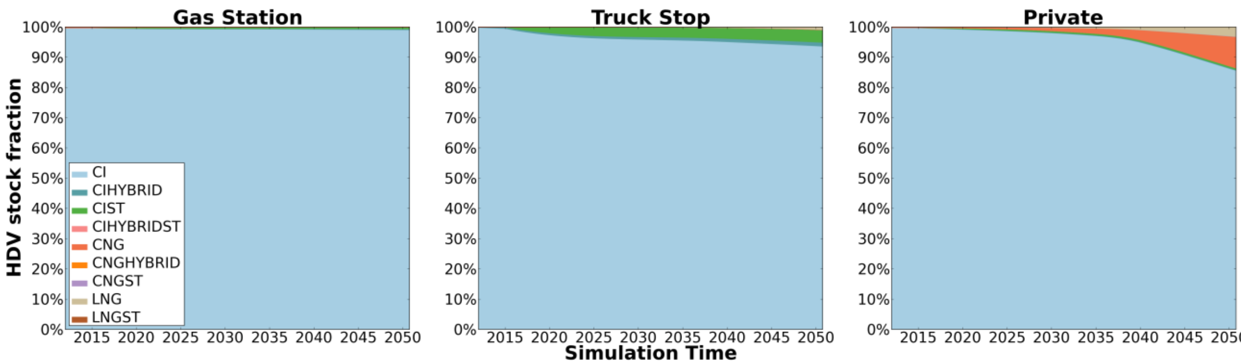


Figure 13: Baseline scenario HDV stock fraction by fueling location.

Figure 14 shows the HDV stock fraction broken out by GVW class. Because class 8 vehicles are larger and often travel longer distances than class 7 vehicles, they consume more fuel annually. Therefore, on average the annual fuel savings from inexpensive natural gas in a class 8 vehicle is greater than in a class 7 vehicle. This difference in savings may be driving more widespread natural gas adoption in the class 8 segment than in the class 7 segment.

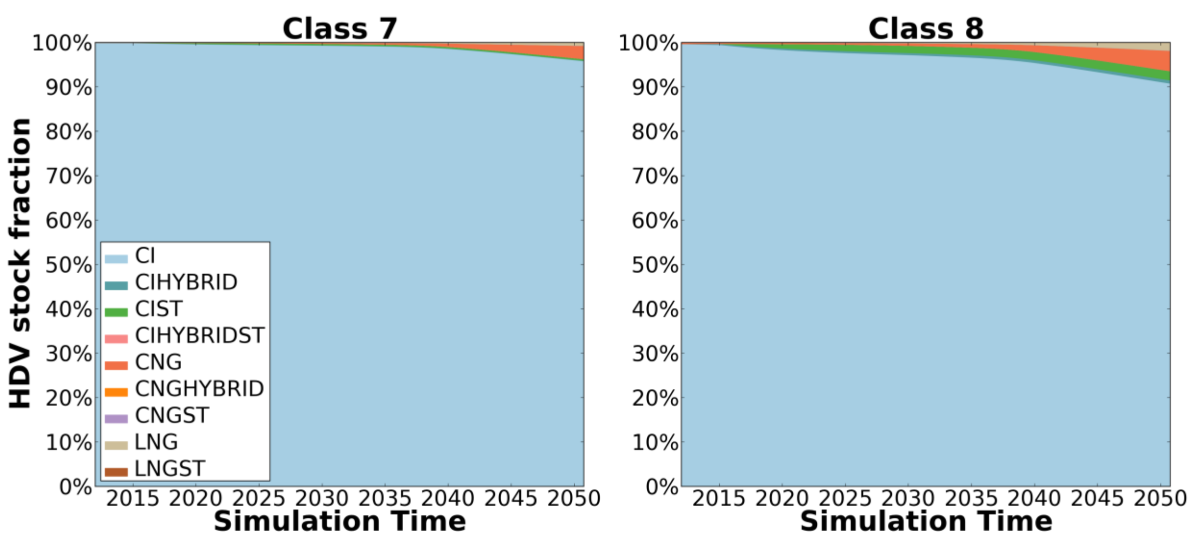


Figure 14: Baseline scenario HDV stock fraction by GVW class.

Figure 15 shows the HDV stock breakdown by fleet size. The model uses longer amortization periods in the financial calculation for the decision model for larger fleets than for smaller fleets to represent the relative access to capital of different types of owners. This variation in amortization period causes larger fleets to adopt alternative fuels and high efficiency technologies more aggressively than small fleets as they are able to wait longer to recoup upfront costs to reap longer term savings.

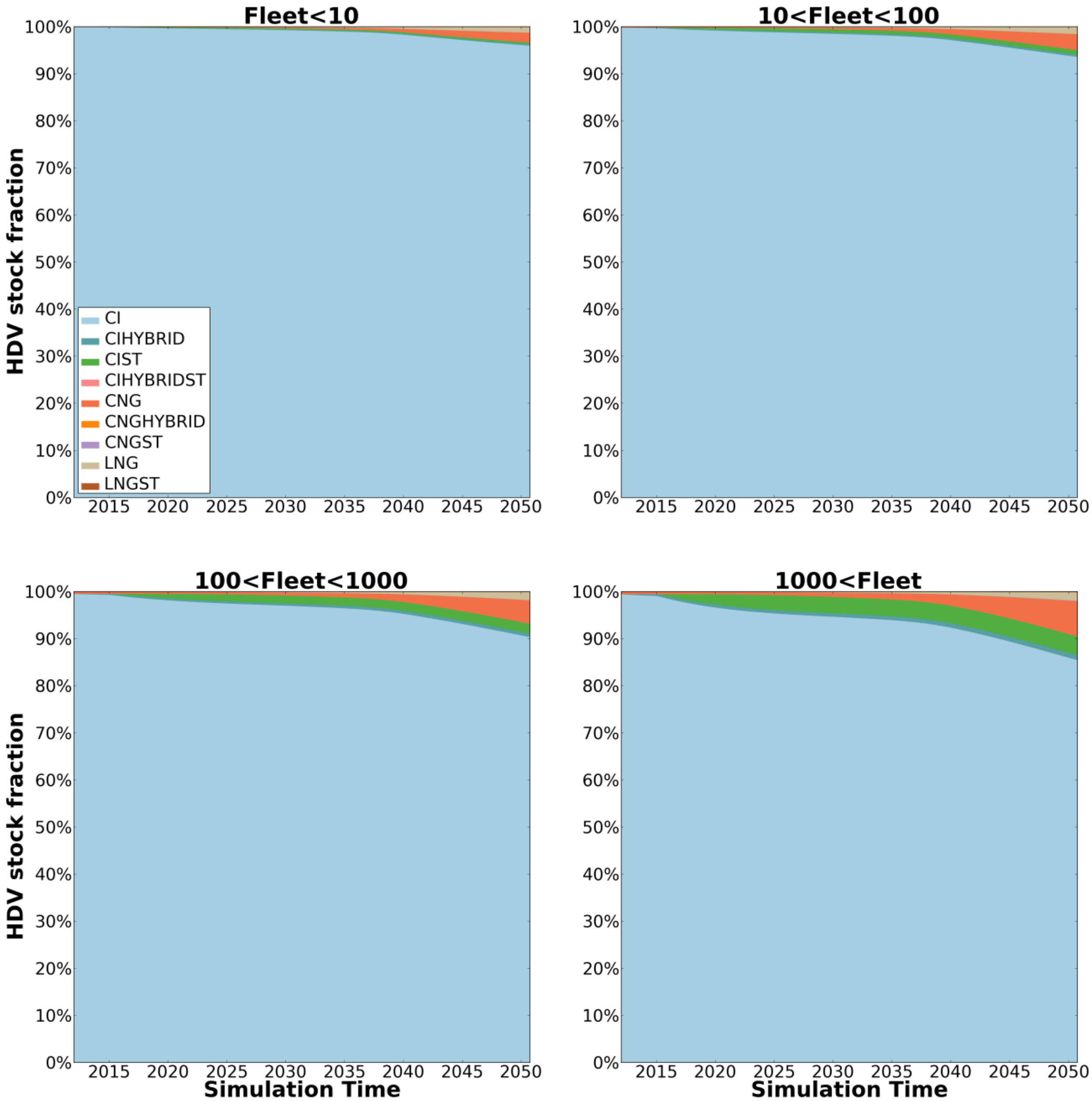


Figure 15: Baseline scenario HDV stock fraction by fleet size.

This baseline scenario provides one sample case of how the HDV sector could progress in the future and provides an illustration of how the model runs. The parametric analysis discussed in the subsequent sections uses 2050 results from several runs with different input parameters to identify which parameters have the most significant impact on the results and to investigate the broad range of possible outcomes.

3.2 Individual Parameter Analysis

This individual parameter analysis addresses the following questions:

- What is the relationship between individual parameters and outputs of interest?
- How would the baseline scenario values change if a specific parameter value was changed?

Single parameter parametric analysis provides insight into the relationship between individual parameters and the outputs of interest. A selection of these relationships is presented in this section to demonstrate this model capability. The figures presented show output values in 2050 as a single parameter is varied. For each analysis, all other parameters are set to the baseline values. 2050 stock figures show how the varied parameter influences the stock profile in 2050 while the 2050 sales figures show how the varied parameter influences the sales profile of the vehicle market in 2050. Fuel profile figures illustrate how the quantity and composition of fuel demand in 2050 is affected by parameter variations. Vertical dashed black lines indicate the baseline value of the varied parameter.

Figure 16 shows how adoption of NGVs increases as oil price increases. At low oil prices, over 95 percent of the vehicles in 2050 use diesel with only a very small fraction of those vehicles being high efficiency vehicles. As oil price increases, that small adoption of high efficiency diesels stays relatively consistent while natural gas driven vehicles take over a portion of the vehicle stock, particularly LNG vehicles at very high oil prices where there is even a small market for high efficiency LNG vehicles. Because LNG is more suitable than CNG for many HDV applications due to its energy density, the more substantial growth in LNG vehicles at high oil prices as compared to CNG vehicles is not surprising. The most dramatic change in the sales and stock profiles occurs in the range of 100 to 400 dollars per barrel indicating a diminishing return on increasing oil prices beyond a certain level. Nevertheless, conventional diesel vehicles are still 70 percent of the stock even when oil prices are double the baseline price, and 60 percent of the stock at triple the baseline price. The sales figure, however, indicates that this majority diesel stock may largely be legacy older vehicles, and with the high sales rates of NGVs at high oil prices, projecting further into the future the stock would continue to shift toward NGVs.

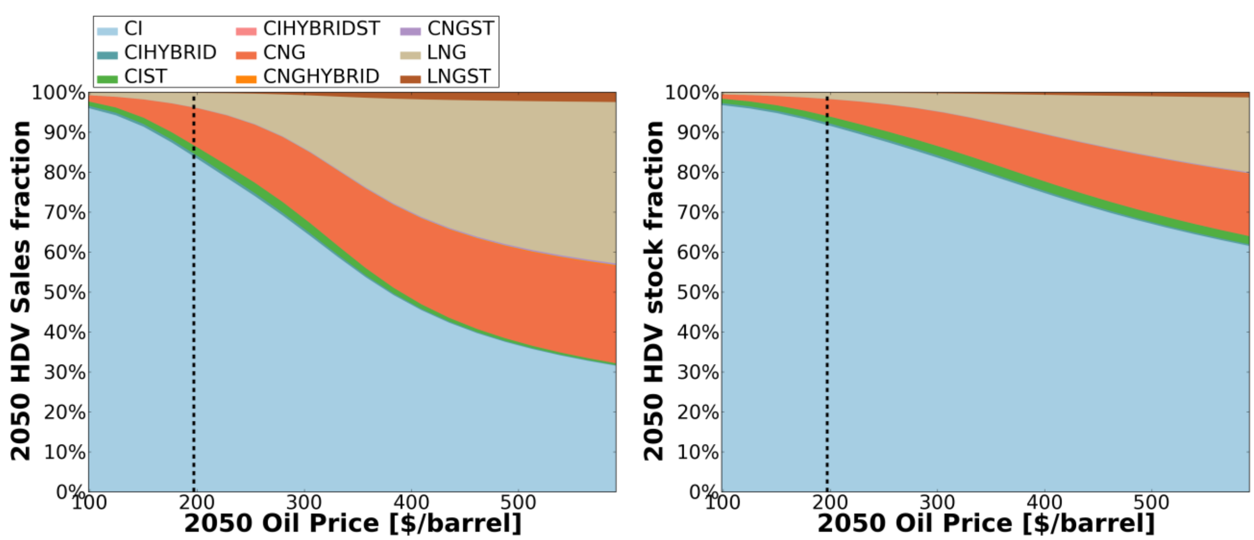


Figure 16: 2050 sales and stock fractions by 2050 oil price.

Figure 17 shows that, as expected, the general sales and stock trends for varied natural gas price are inverted as compared to the oil price variation. However, at baseline oil prices and very low natural gas prices, NGVs comprise only a little over 10 percent of the vehicle stock which is a smaller fraction than at baseline natural gas prices and high oil prices. As would be expected, natural gas price increases, the fraction of NGVs declines and at twice the baseline natural gas price, NGVs comprise only a few percent of the vehicle stock.

At the high end of natural gas price, very few NGVs are present in the 2050 stock, but the sales market for high efficiency diesel vehicles reaches over 5 percent. The trends shown in Figure 16 and Figure 17 collectively indicate that the relative price of oil and natural gas will influence whether natural gas or high efficiency diesel will be the most attractive alternative vehicle option. NGVs are not only in competition with standard diesel vehicles but also their high efficiency counterparts.

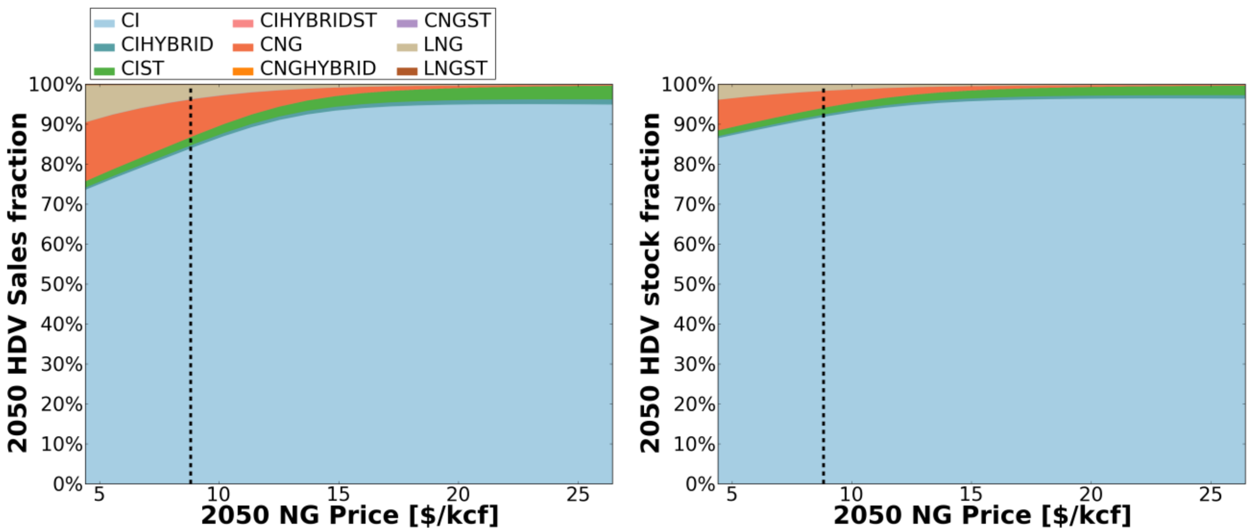


Figure 17: 2050 sales and stock fractions by 2050 natural gas price.

By comparison with the fleet profile plots shown in Figure 16 and Figure 17, the fuel profiles shown in Figure 18 indicate that at high oil prices or low natural gas prices, the vehicles segments adopting natural gas are the highest fuel consumers. The total fuel consumed remains fairly constant over both parameters while the diesel fraction of fuel consumed is significantly driven by both oil and natural gas prices.

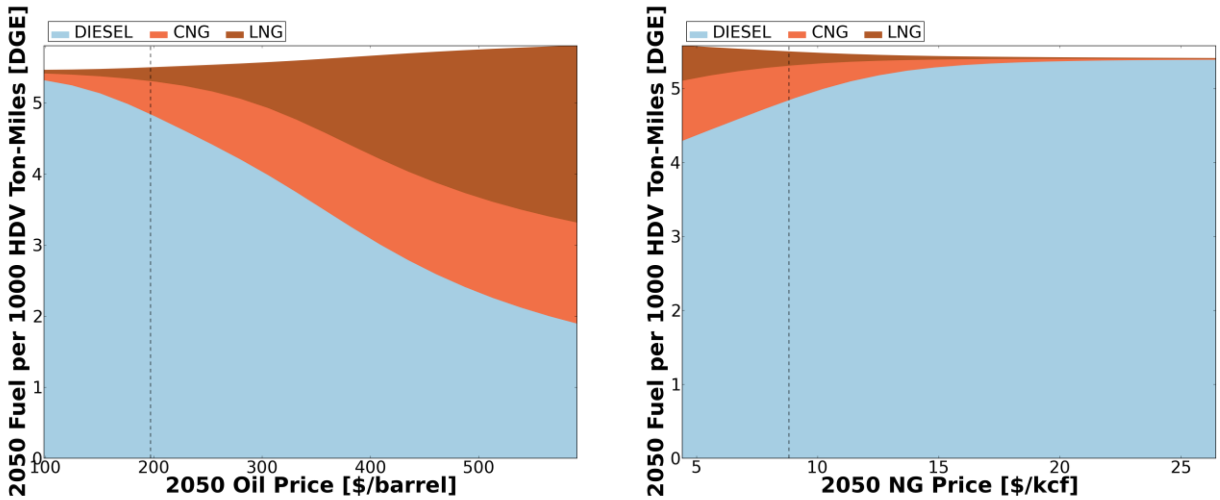


Figure 18: 2050 fuel used per 1000 HDV ton-miles by oil and natural gas price.

As shown in Figure 19, an influential mechanism for driving down fuel consumption is through increasing internal combustion engine (ICE) efficiency. Increasing ICE efficiency results in decreased adoption of NGVs and high efficiency technologies due to lower potential fuel cost savings, but dramatically decreases the total quantity of fuel consumed as well as the quantity of each individual fuel consumed.

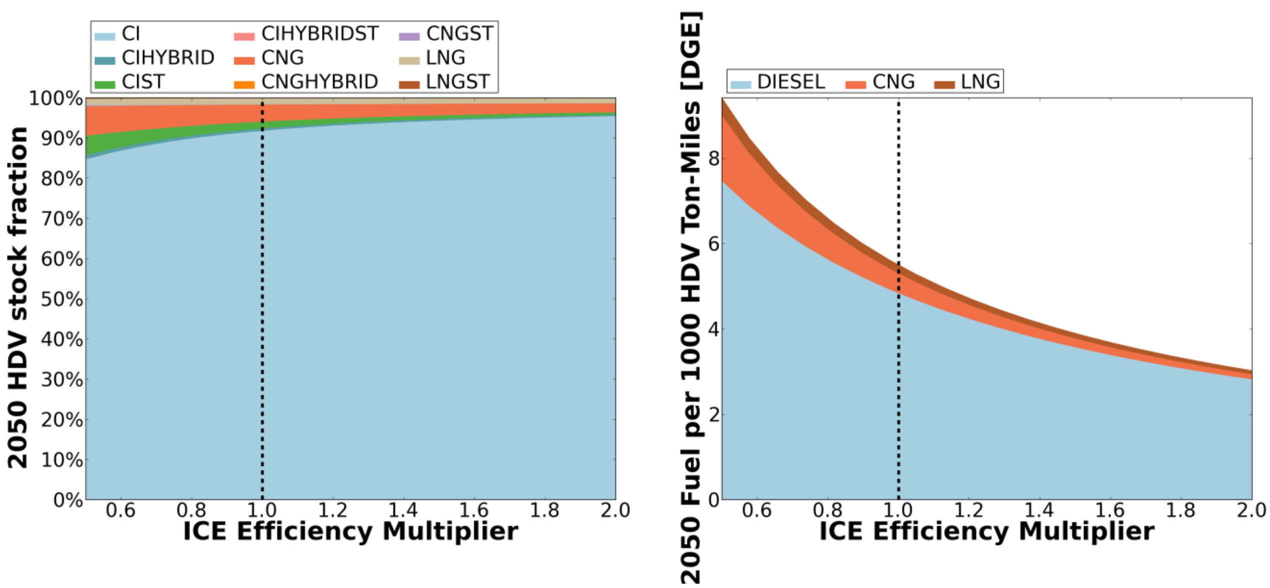


Figure 19: 2050 HDV stock fraction and fuel used per 1000 HDV ton-miles by internal combustion engine efficiency multiplier.

To investigate the market potential of high efficiency (SuperTruck-like) technologies, the cost of these technologies was varied as shown in Figure 20. Due to the low adoption rates at the baseline cost, increasing the cost has little impact. Reducing the cost from the baseline level, however, does encourage adoption of these technologies across fuel types and particularly for the natural gas (NG) segments which are both almost entirely replaced by high efficiency versions at low high efficiency cost. However, given the relatively high price of diesel, the relatively low overall adoption of efficiency technologies for diesel vehicles as a fraction of total diesel vehicles is interesting. Figure 21 shows that the more efficient diesel options, including both the high efficiency and the high efficiency hybrid versions combined, achieve approximately a 30 percent penetration in the gas station refueling segment but a nearly 50 percent penetration in the truck stop refueling segment at low high efficiency costs. The higher annual fuel costs for the truck stop refueling segment drives this increase interest. Decreases in total fuel consumption and diesel consumption occur at the low end of high efficiency cost.

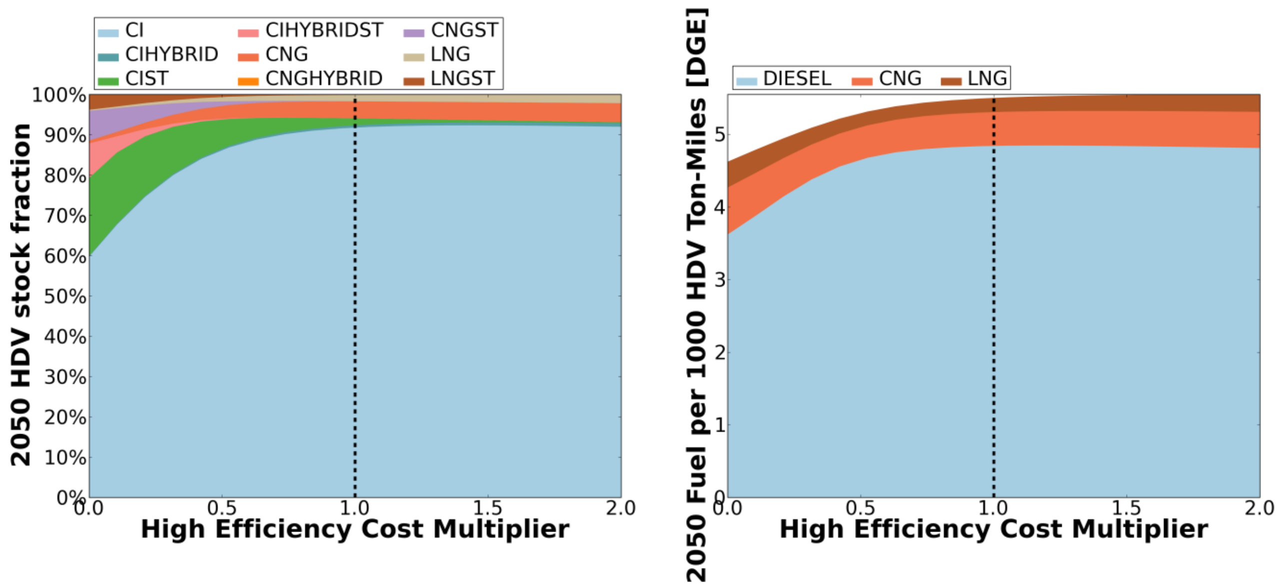


Figure 20: 2050 HDV stock fraction and fuel used per 1000 ton-miles by high efficiency cost multiplier.

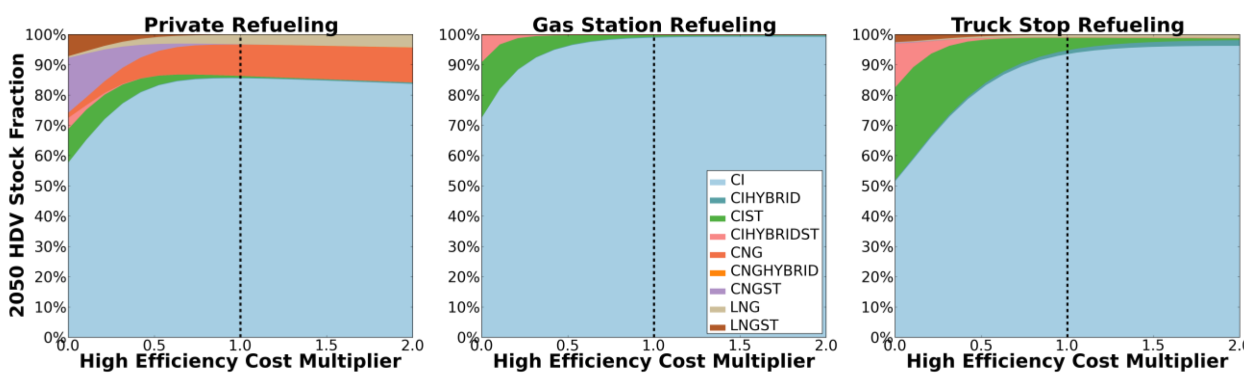


Figure 21: 2050 HDV refueling type stock fractions by high efficiency cost multiplier.

Figure 22 considers the 2050 stock fraction and fuel profile resulting from varying the efficiency gain from the high efficiency technologies as compared to varying the cost of these technologies as shown in the previous figure. As the high efficiency technologies become increasingly effective, diesel high efficiency vehicles appear to displace both some standard diesels as well as some NGVs. Neither LNG nor CNG high efficiency vehicles appear in the vehicle stock. These trends result in small decreases in diesel and total fuel consumption.

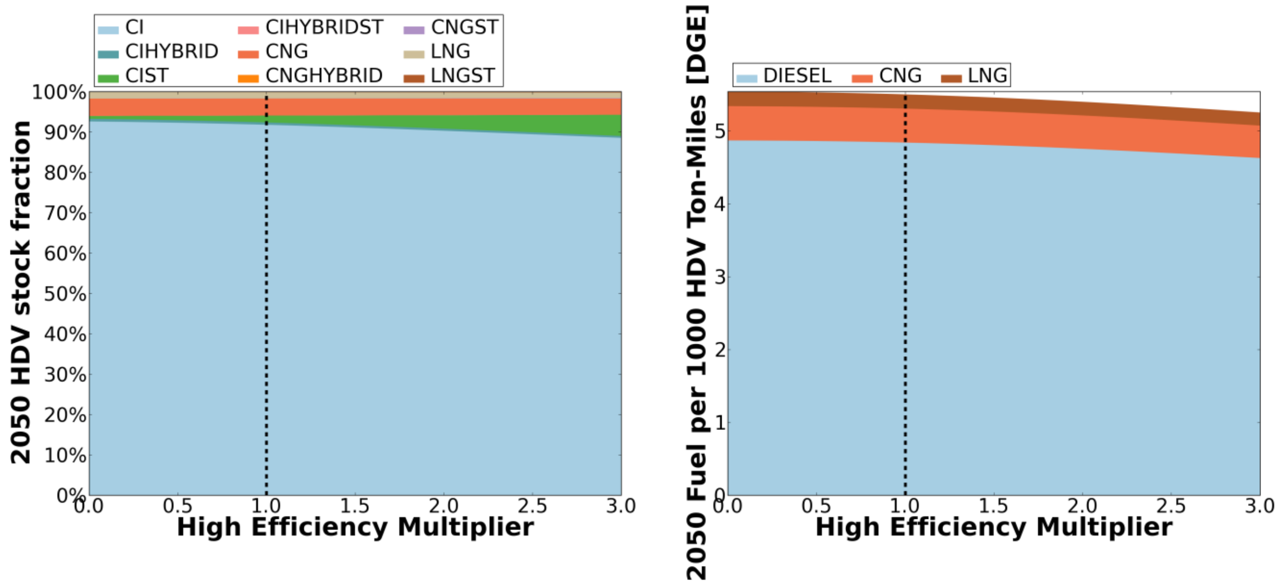


Figure 22: 2050 HDV stock fraction and fuel used per 1000 ton-miles by high efficiency multiplier.

Figure 23 and Figure 24 show the influence of the cost premium for NGVs. Clearly the NGV cost influences the adoption of NGVs, particularly in the private refueling segment. The truck stop refueling segment also has some LNG adoption at low NGV cost. NGV cost also has an interesting influence on high efficiency vehicle adoption, causing a small peak in total fuel consumption at an NGV cost multiplier value around 0.5. This peak arises because at the low end of NGV cost high efficiency NGVs are adopted and at high NGV cost the NGV segment is partially replaced with high efficiency diesels.

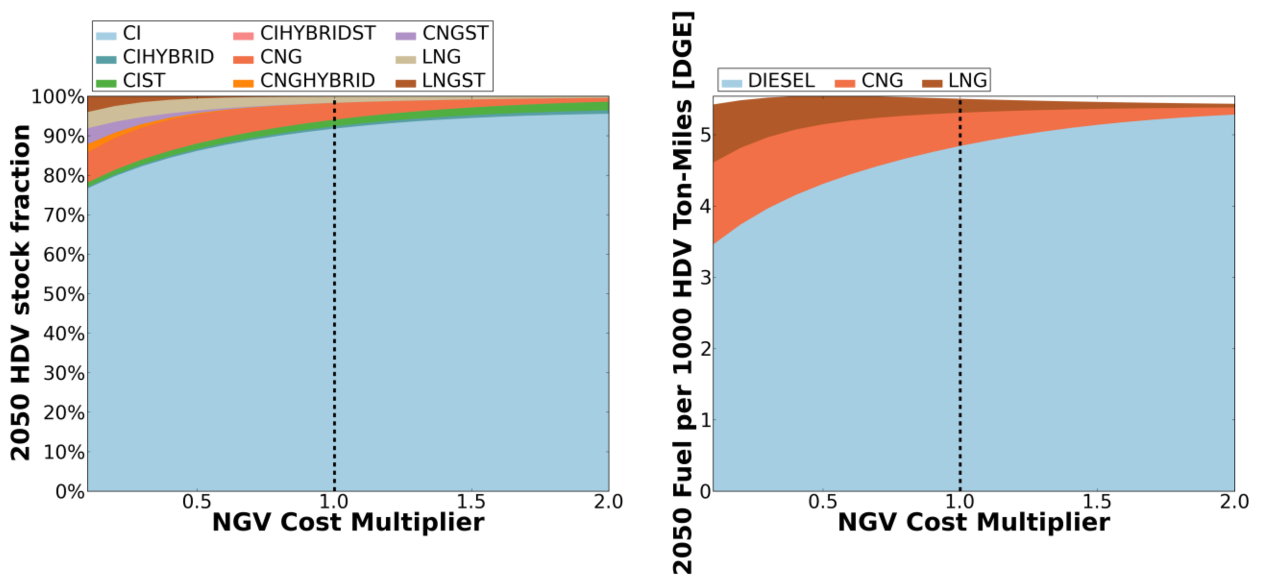


Figure 23: 2050 HDV stock fraction and fuel used per 1000 ton-miles by NGV cost multiplier.

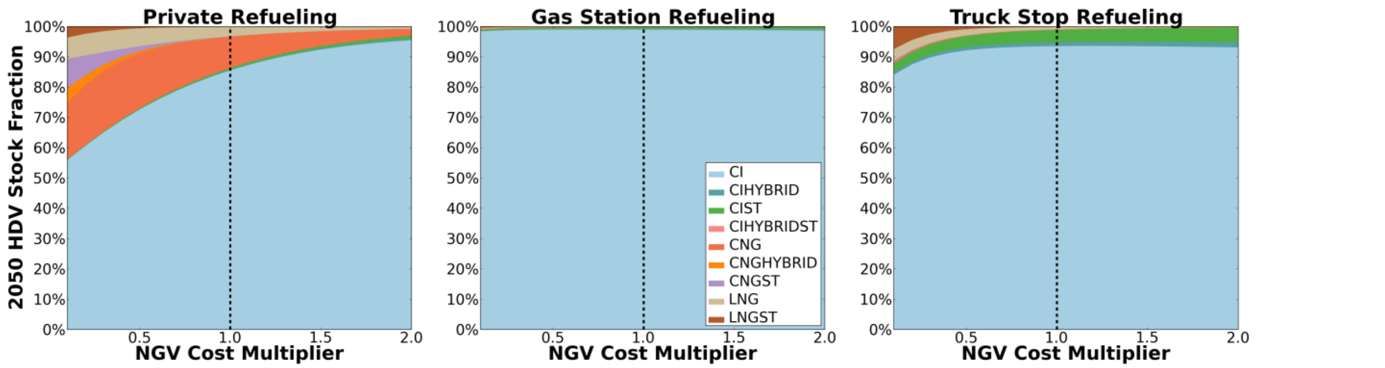


Figure 24: 2050 HDV stock fraction for refueling segments by NGV cost multiplier.

The influence of the payment period is considered through varying the mean payment period which scales both the large and small payment periods accordingly to obviate the need to scale both independently. As shown in Figure 25, payment period is positively related to both natural gas and efficiency technology adoption. From a 1 year payment period to a 10 year payment period, the fraction of standard diesel vehicles decreases from almost 95 percent to approximately 40 percent. For a payment period shift from 1 to 3 years, the fraction of standard diesel shifts to both natural gas and high efficiency diesels, while for larger payment periods, the dominant shifts are toward adoption of efficiency technologies among all fuel types. Three years is a significant timeframe in that long range line haul tractor-trailers are often sold after 3 to 5 years of operation and converted to other uses. If natural gas operation or high efficiency technologies do not recoup their costs in the resale market, these payment period lengths can be considered an upper bound on acceptability for an initial owner of these vehicles. At a payment period of five years, standard diesel powertrains are still approximately 60 percent of the 2050 vehicle stock and 45 percent of 2050 vehicle sales. High efficiency technologies comprise a substantial fraction of the alternatives in at a 5 year payback period.

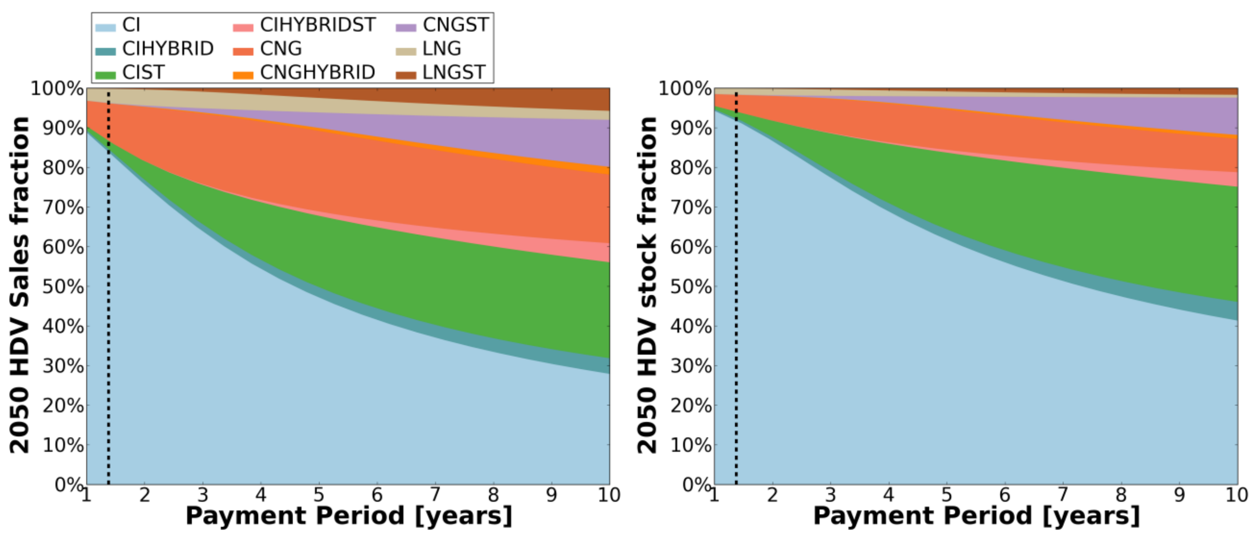


Figure 25: 2050 HDV sales and stock fractions by payment period.

Figure 26 shows how this stock fraction breaks down by refueling station. NGVs (CNGs and CNGSTs in particular) are more prevalent among the private refueling segment because they can take advantage of private infrastructure development and overnight refueling. Both the gas station and truck stop refueling segments have large fractions of high efficiency diesel vehicles at long payment periods. In the truck stop refueling segment, the increased efficiency diesel powertrains combined account for 70 percent of the vehicle stock at a 10 year payment period. These technologies are attractive in this segment due to their high annual fuel consumption.

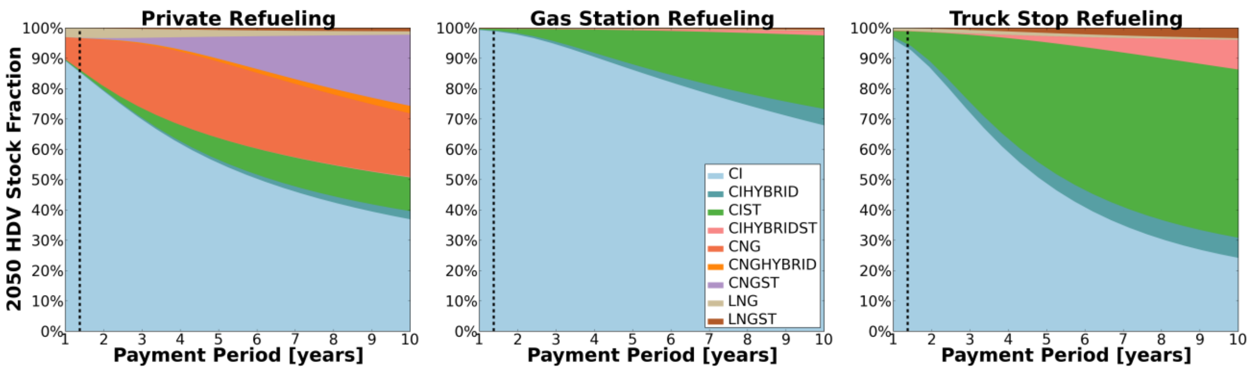


Figure 26: 2050 HDV stock fractions for refueling segments by payment period.

As shown in Figure 27, for vehicles that refuel at private refueling stations, the cost of installing fueling infrastructure is a significant consideration. As the cost to construct onsite natural gas fueling infrastructure increases, diesel and diesel high efficiency vehicles are increasingly popular while NGVs of all types become a very small fraction of the vehicle stock.

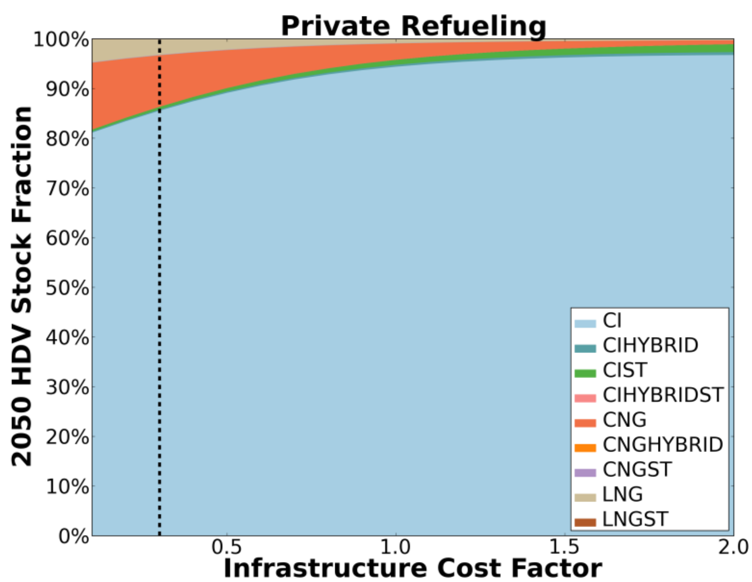


Figure 27: 2050 HDV private refueling stock fraction by infrastructure cost factor.

To investigate the degree to which infrastructure availability is important, the infrastructure willingness factor, which characterizes the number of alternative fuel stations relative to diesel stations that must exist before 50 percent of new vehicles will consider the alternative fuel, was varied. As shown in Figure 28, due to the small number of alternative fuel vehicles refueling at public stations, varying this parameter under otherwise baseline conditions appears to have little influence. However, the small but increasing fraction of NGVs as the infrastructure willingness factor moves from the baseline to very low values indicates this parameter is somewhat influential and may be more influential under other conditions, especially as varied at the low end.

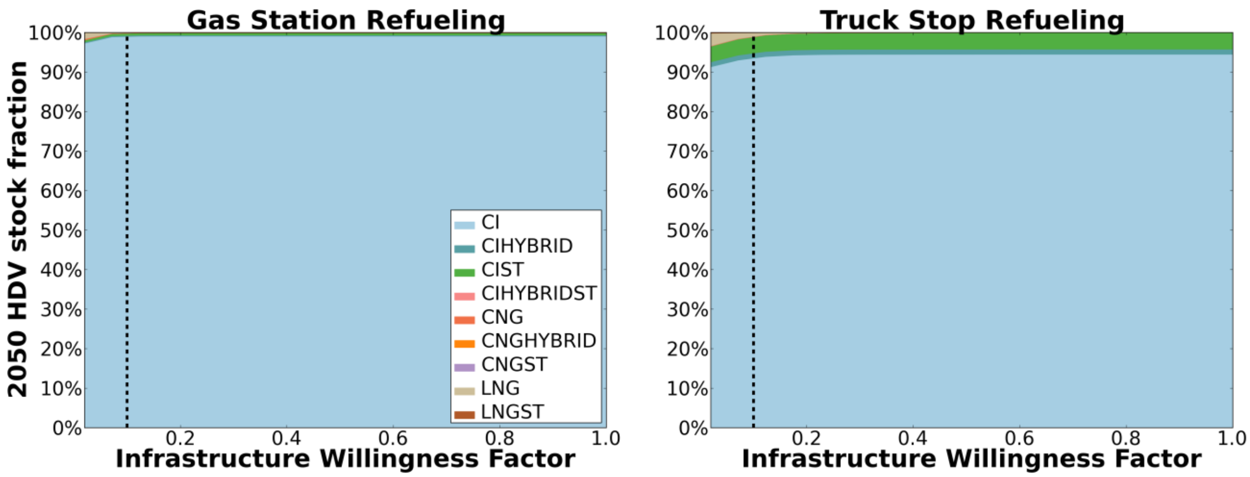


Figure 28: 2050 HDV stock fraction for gas station and truck stop refueling vehicles by infrastructure willingness factor.

3.3 Sensitivity Analysis

This sensitivity analysis addresses the following questions:

- Which inputs most strongly influence outputs of interest?
- Which uncertainties matter most?
- Which levers could be most useful in directing desirable outcomes?

Varying multiple parameters enables the identification of relationships between parameters. Because varying limited sets of parameters may miss combinations of parameters that yield unexpected or extreme results, varying all parameters simultaneously allows for more thorough identification of the influence of each parameter. Latin hypercube sampling analysis is used to interrogate the parameter space, and Spearman correlation coefficients are calculated to identify the parameters with the most direct influence on the outputs. This analysis indicates which model uncertainties may be most important to narrow down as well as which levers may be best utilized to bring about desired outcomes.

One of the objectives of this analysis is to identify what factors most significantly impact fuel consumption, and more specifically diesel consumption. Figure 29 shows the Spearman correlation coefficients representing the degree to which model parameters are monotonically related to consumption of each fuel per ton-mile in 2050. Because the total number of ton-miles in 2050 is constant, these results also correspond to total fuel consumption. ICE efficiency is clearly the most significant parameter in determining total fuel and diesel consumption. Diesel consumption is also sensitive to oil price and natural gas price, indicating that relative fuel prices and overall vehicle efficiency may be the most significant drivers to reducing diesel consumption.

Alternative fuel use is also relatively insensitive to station growth as compared to the infrastructure willingness factor because even at the fastest station growth rates do not impact number of alternative fuel stations with respect to the number of diesel stations on the order of the infrastructure willingness parameter range. Therefore the infrastructure willingness parameter dominates the relationship between alternative fueling stations and alternative fuel use. Infrastructure cost and relative fuel prices are also important factors in LNG and CNG use.

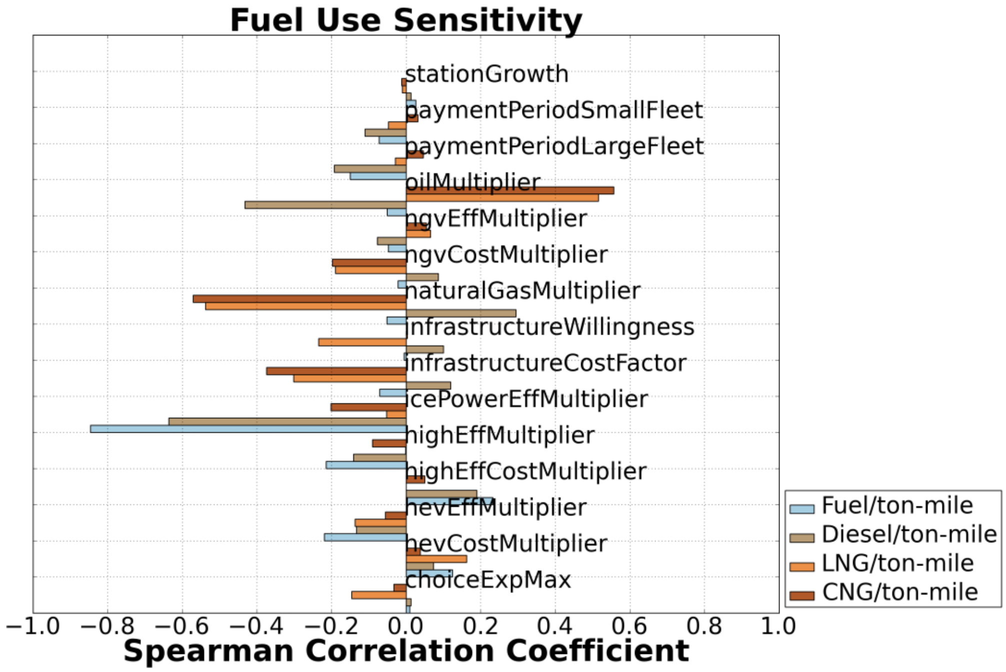


Figure 29: Sensitivity of 2050 fuel per ton-mile to model parameters.

The sensitivity of four emissions types of concern to the model parameters is shown in Figure 30. Because emissions are calculated based on fuel consumption, the sensitivity of the various types of emissions to the parameters is generally consistent across emissions types and follows the trends of the fuel use sensitivity figure, more specifically paralleling total fuel and diesel consumption correlation coefficients. One notable exception to these parallels is with regard to PM2.5, which is more sensitive to the relative fuel costs than the other emissions and in fact increases with increasing oil price.

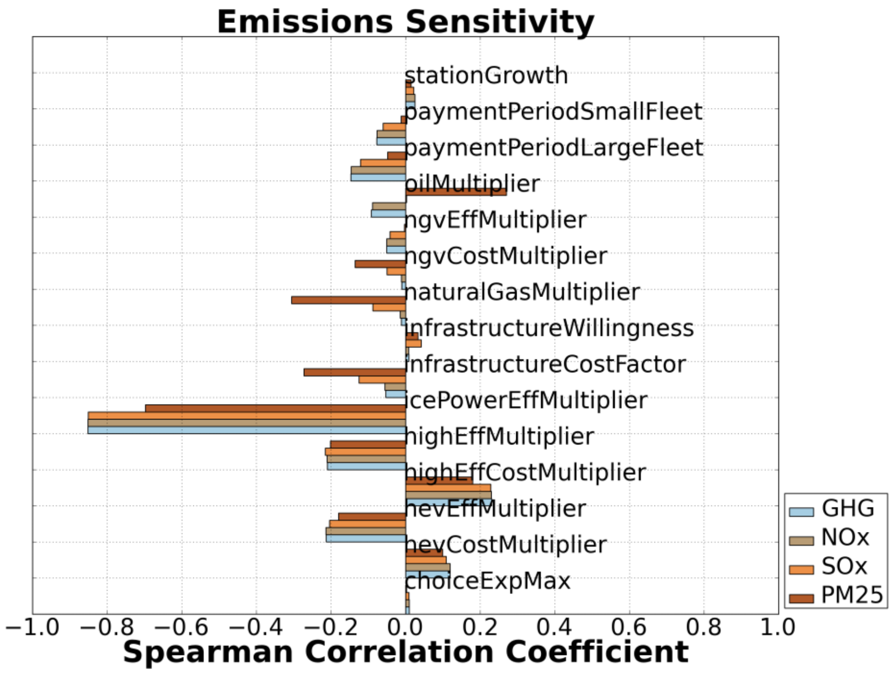


Figure 30: Sensitivity of emissions to model parameters.

Figure 31 and Figure 32 show to which parameters hybrid and high efficiency technology adoption are most sensitive. Hybrids (total, diesel, and natural gas) are consistently most sensitive to the cost and efficiency of the technology. Natural gas hybrids are also sensitive to the NGV price due to the natural gas hybrid vehicle cost being the sum of the natural gas and hybrid premium cost values. Further, NG hybrids are sensitive to fuel prices and infrastructure costs, parameters to which NGV adoption in general is sensitive. Diesel hybrids are also sensitive to large fleet payment period, which impacts the financial attractiveness of efficiency options.

The parameter sensitivities of high efficiency (SuperTruck) technologies follow a similar pattern to the hybrid sensitivities, with the obvious exception of sensitivity to the cost and efficiency of these technologies as opposed to hybrid technologies. These technologies are more sensitive to payment period than the hybrid technologies due to their higher initial cost and larger long-term returns.

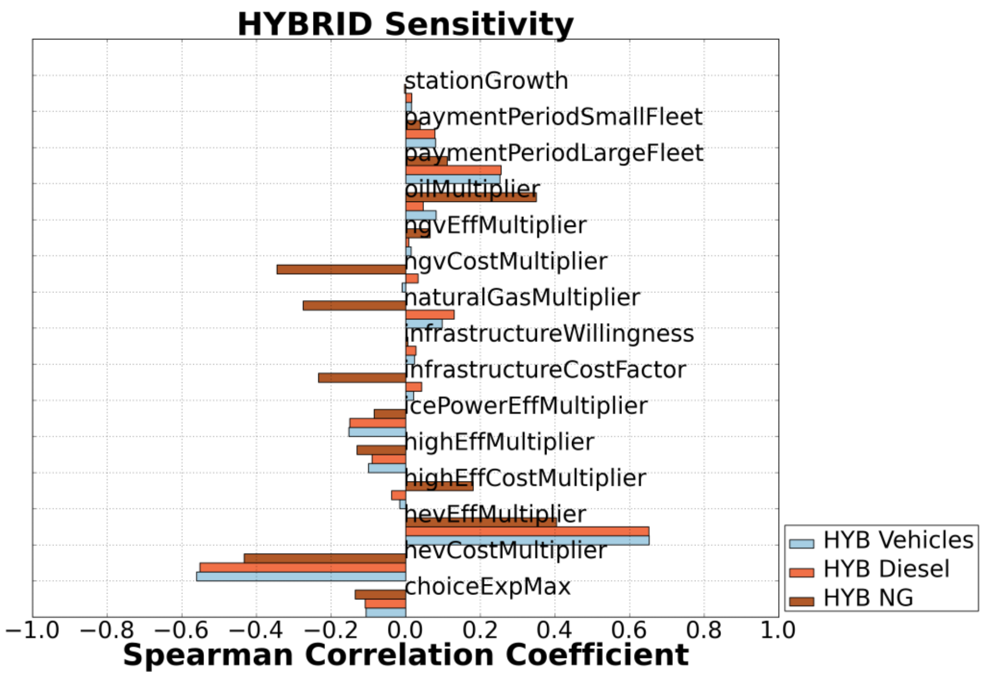


Figure 31: Sensitivity of hybrid vehicle adoption to model parameters.

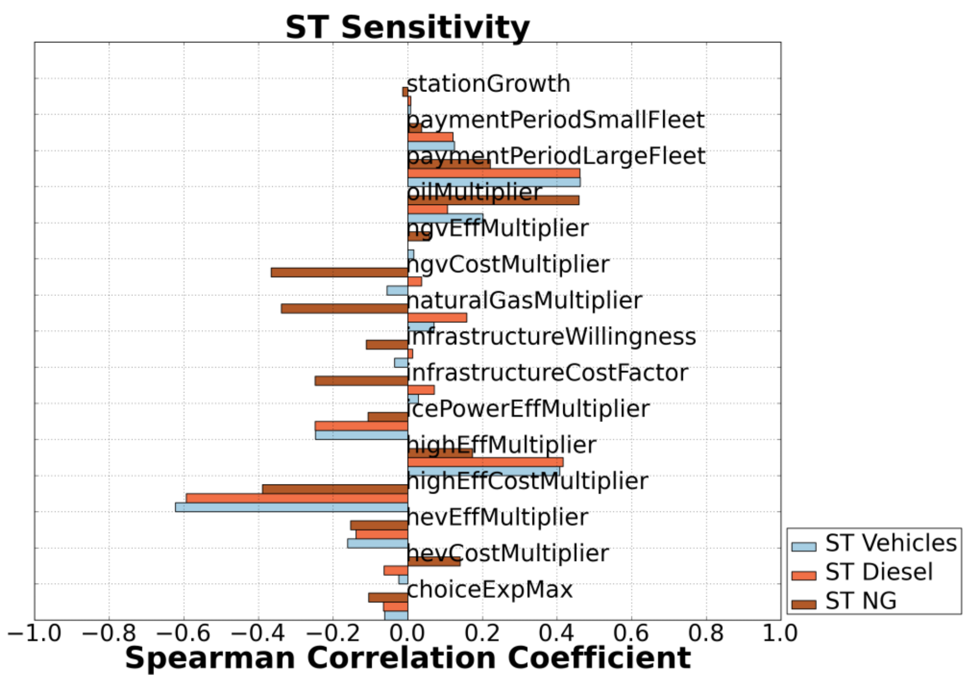


Figure 32: Sensitivity of high efficiency vehicle adoption to model parameters.

As shown in Figure 33, the adoption of NGVs is most sensitive to oil and natural gas prices as well as, the infrastructure cost factor. This first observation agrees with the generally held expectation that the fuel price differential which drives the potential for operating cost savings over time will be the driving factor for moving to NGVs in the HDV sector. Infrastructure willingness is also an important factor for the LNGs that fuel at public truck stops, as compared to CNGs which largely emerge in the private refueling sector and are therefore more sensitive to the cost of constructing private infrastructure.

NGV adoption is also sensitive to the cost of the NGVs, but less so than to the natural gas price. NGV adoption is only mildly sensitive to high efficiency and hybrid technology efficiencies and costs, which may be because although under some conditions high efficiency diesel vehicles may appear to displace NGVs, when high efficiency technologies are generally attractive, they are adopted both for diesel as well as natural gas powertrains.

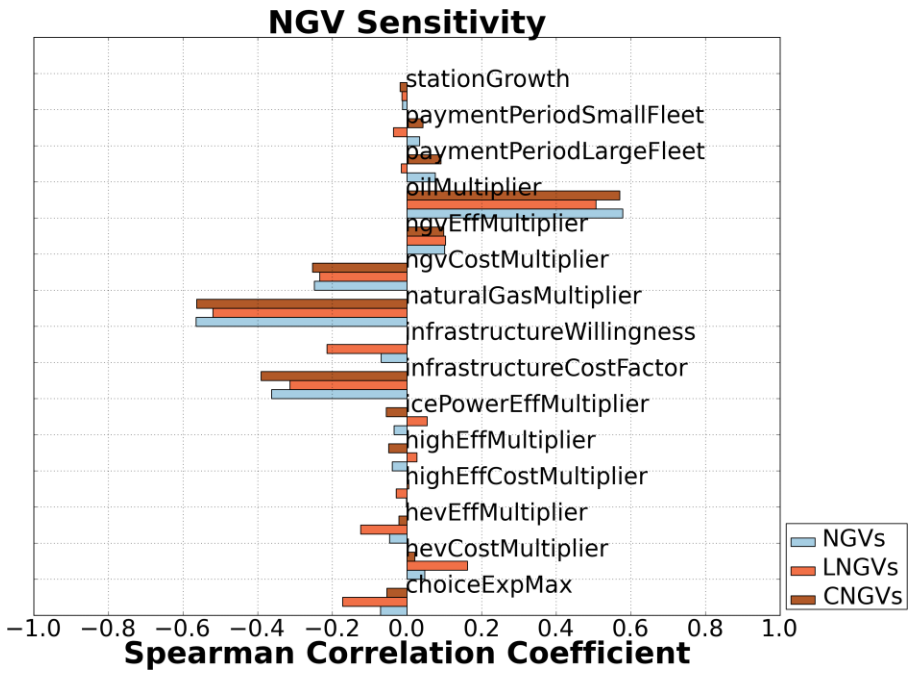


Figure 33: Sensitivity of NGV adoption to model parameters.

Figure 34 shows the sensitivities of the adoption of LNG or CNG by refueling segment and how these sensitivities are different for the different fuel types and refueling segments. These sensitivities parallel those from the previous plot, with the infrastructure willingness sensitivity of the truck stop LNG vehicles strongly demonstrated, confirming the assertions about the mechanisms driving the sensitivity results.

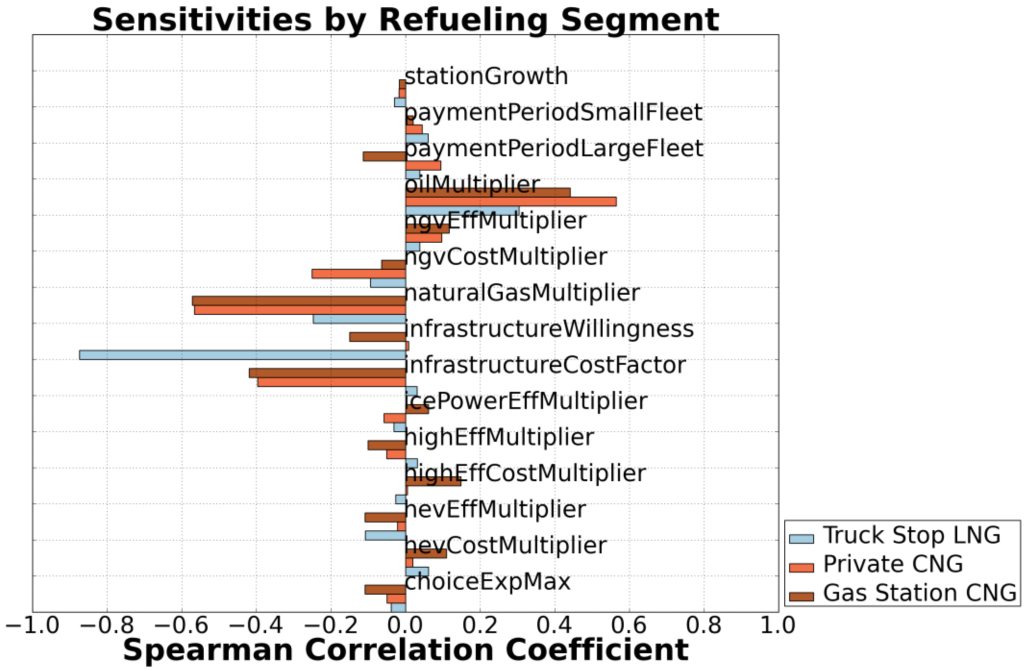


Figure 34: Sensitivity of HDV refueling segments to model parameters.

3.4 Trade space analysis

This trade space analysis addresses the following questions:

- How do future natural gas and oil prices influence the adoption of NGVs and high efficiency technologies?
- How do natural gas and high efficiency technologies compete with each other in the market?
- What is the market for natural gas, hybrid, and high efficiency vehicles for varied costs and efficiencies?

These questions are also considered with respect to how the resultant vehicle stock affects other outputs of interest, particularly diesel consumption and GHG emissions.

3.4.1 Analysis of the influence of future natural gas and oil prices on the adoption of natural gas vehicles and high efficiency technologies

Future fuel costs are uncertain parameters and therefore it is important to investigate the impact of the relative natural gas and oil prices on the future of the HDV sector. It is generally believed that low natural gas prices may drive HDVs toward natural gas. As expected, this trend is clearly visible in Figure 35 and Figure 36. As oil prices rise and natural gas prices decline, diesel consumption decreases and natural gas consumption increases dramatically while the fraction of the 2050 HDV vehicle stock that uses diesel declines from 95 percent to 55 percent.

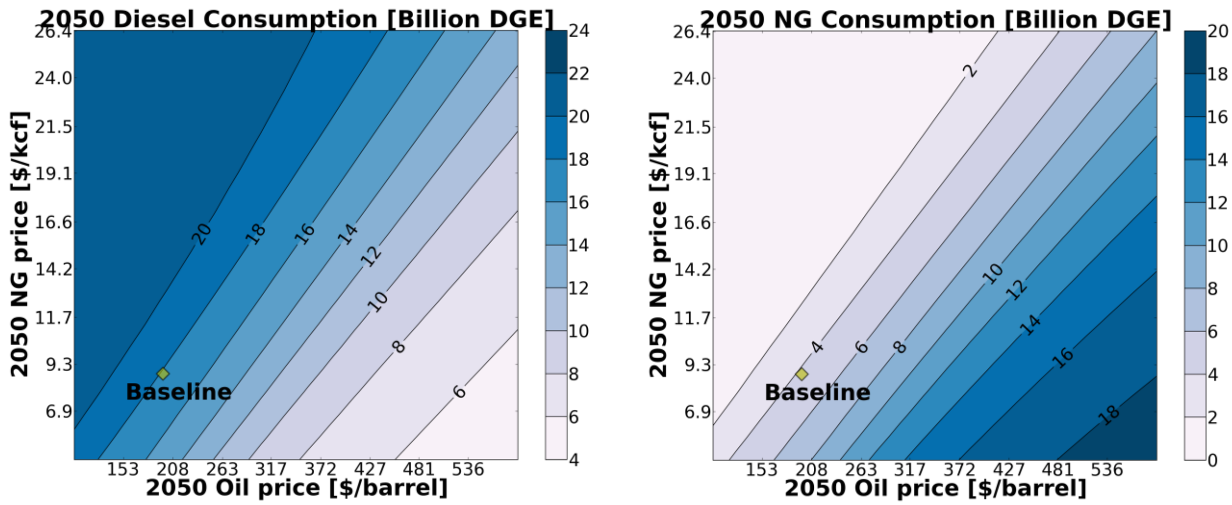


Figure 35: 2050 diesel stock fraction and natural gas consumption by 2050 natural gas and oil prices.

Figure 36 highlights that total diesel consumption declines more rapidly than the diesel stock fraction as NGVs penetrate the long haul (i.e. higher annual fuel consumption) segments of the HDV sector.

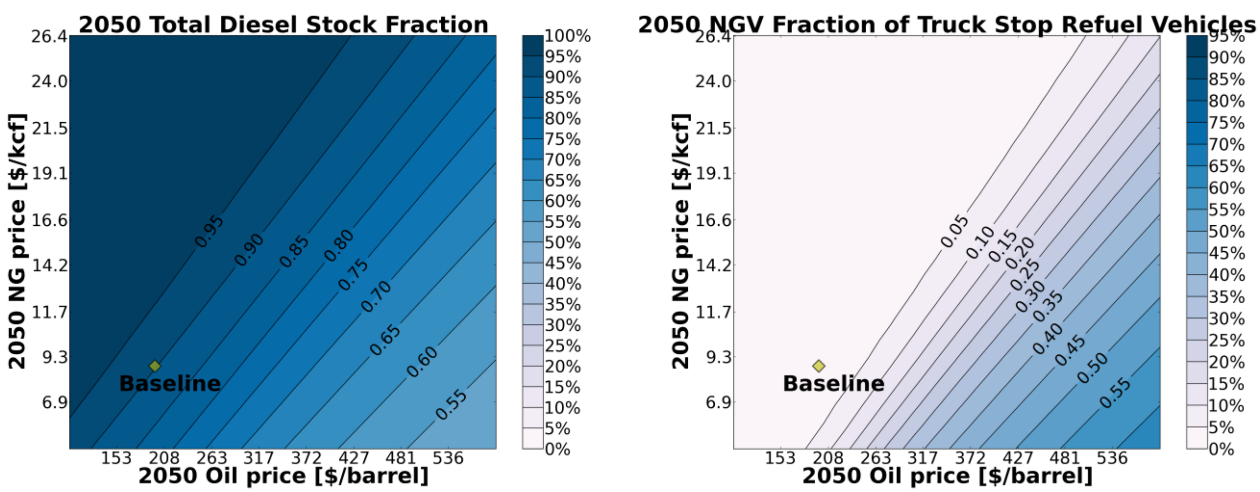


Figure 36: 2050 diesel consumption and fraction of truck stop refueling (long haul) vehicles using natural gas by 2050 natural gas and oil prices.

As shown in Figure 37, high efficiency technologies reach 18 percent vehicle stock adoption at high natural gas and oil prices. Figure 38 shows the breakdown of these high efficiency vehicles according to their fuel type. High efficiency diesel vehicles achieve over double the peak adoption fraction of natural gas high efficiency vehicles over this parameterization range.

At high natural gas and oil price, diesel high efficiency powertrains achieve their highest adoption. However, natural gas high efficiency vehicle adoption is more dependent on increasing oil price than increasing natural gas price and actually decreases at very high natural gas price. This decrease at high natural gas price is likely due to the decrease in total NGVs when this fuel is expensive.

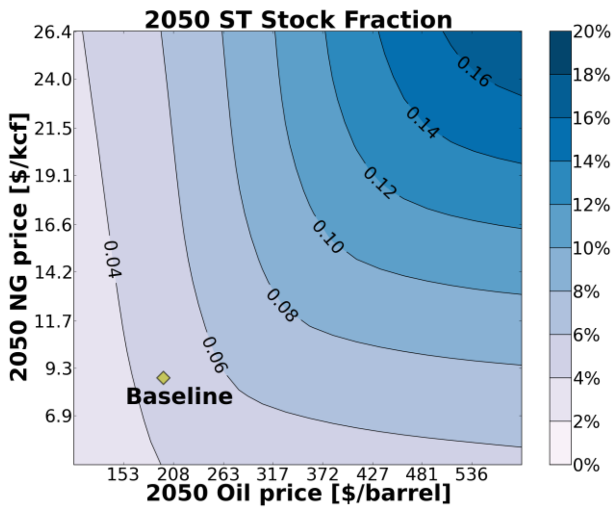


Figure 37: 2050 high efficiency vehicle stock fraction by 2050 natural gas and oil prices.

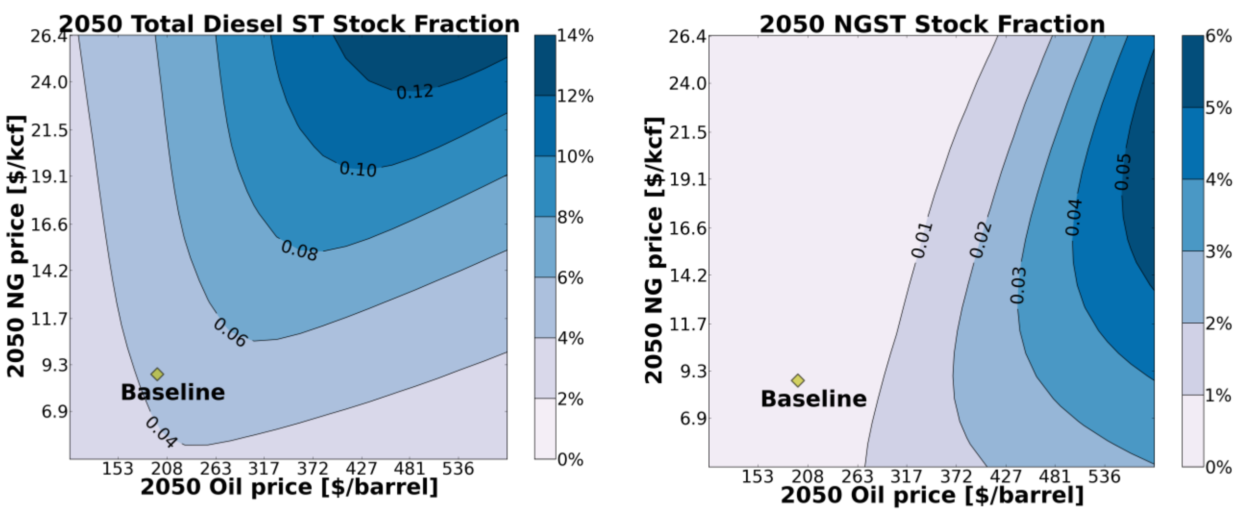


Figure 38: 2050 diesel and natural gas high efficiency vehicle fractions by 2050 natural gas and oil prices.

As shown in Figure 39, reduction in GHG emissions follows the pattern of high efficiency powertrain adoption with small influence on relative diesel versus natural gas consumption. As both fuels are carbon-intensive, the shift to natural gas provides little advantage compared to the increased stock efficiency provided by the high efficiency vehicle adoption.

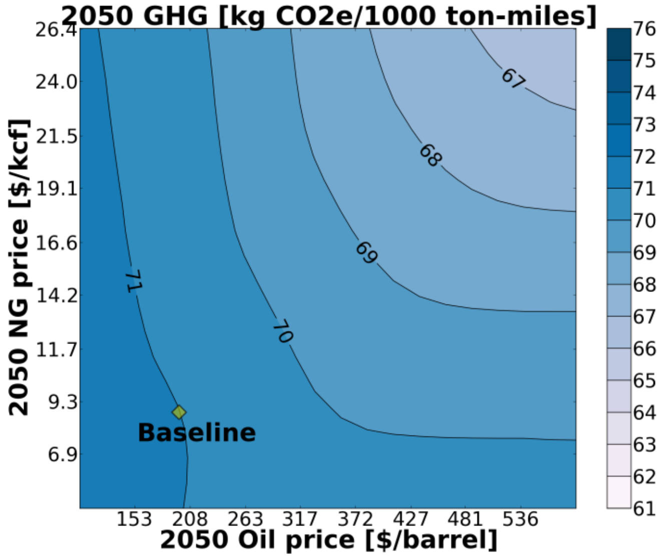


Figure 39: 2050 GHG by 2050 natural gas and oil prices.

ICE efficiency interacts with natural gas and oil prices to influence the vehicle stock through influencing vehicle fuel consumption and thereby vehicle operating cost. Figure 40 illustrates this relationship and how it influences adoption of natural gas and high efficiency vehicles. NGVs achieve highest adoption rates at low ICE efficiency and high oil price because this is the combination of parameters yielding the highest diesel vehicle operating cost thus incentivizing NGV adoption. At oil prices up to twice the baseline value, both oil price and ICE efficiency influence high efficiency vehicle adoption; however, at higher oil prices low ICE efficiency more significantly drives high efficiency vehicle adoption.

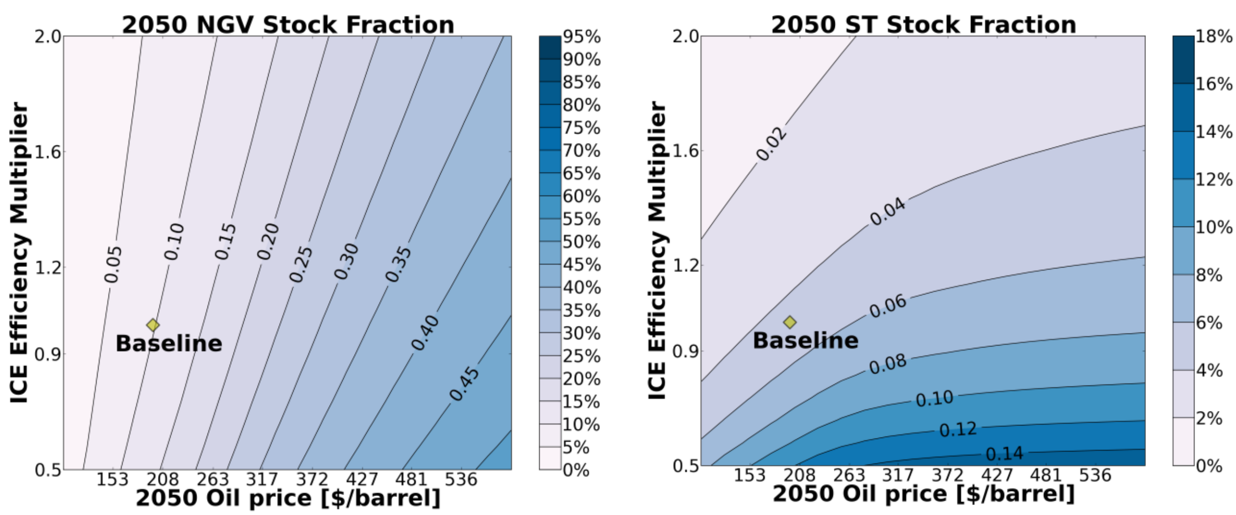


Figure 40: 2050 natural gas and high efficiency stock fractions by 2050 oil price and internal combustion engine efficiency.

Figure 41 shows that GHG emissions are largely insensitive to oil price as compared to ICE efficiency, indicating again that the shift to NGVs as oil price increases is less impactful to GHG emissions reduction than the overall efficiency of the HDV stock. Doubling ICE efficiency decreases GHG emissions by 40 percent irrespective of oil price.

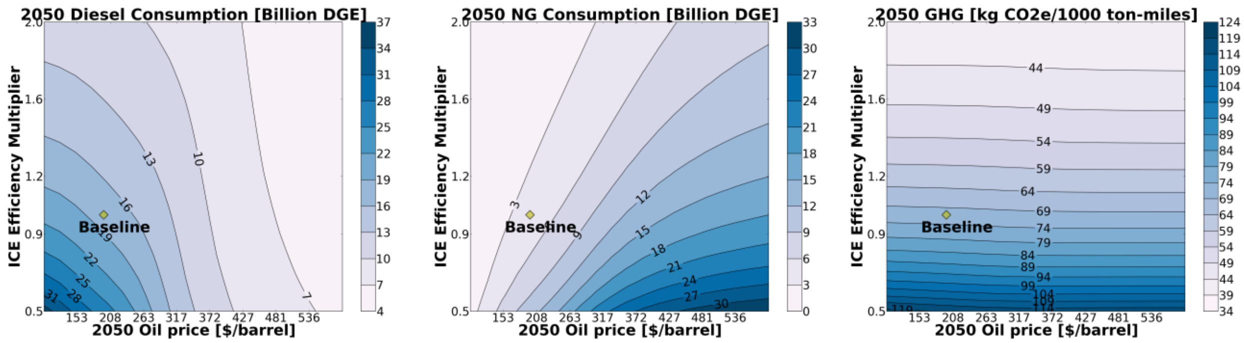


Figure 41: 2050 diesel consumption, natural gas consumption, and GHG emissions by 2050 oil price and internal combustion engine efficiency.

Oil price, natural gas price, and ICE efficiency all significantly influence diesel consumption, but GHG emissions are substantially impacted only by increasing stock efficiency, either through increasing overall ICE efficiency or increasing adoption of high efficiency vehicles which is increased at high oil and natural gas prices. Oil price and natural gas price are particular drivers for natural gas adoption among the truck stop refueling segment due to this segment having the highest fuel consumption. Increasing ICE efficiency substantially decreases adoption of high efficiency vehicles but has much less influence on NGV adoption.

3.4.2 Analysis of market competition between natural gas vehicles and high efficiency technologies

NGVs and high efficiency technologies both have high initial costs but promise long term savings. Thus, they may compete in the marketplace based on the relative cost savings each can offer over a standard diesel vehicle. Figure 42 shows that high efficiency vehicle adoption is primarily driven by the cost of the efficiency technologies and is only affected by NGV cost at low values of that parameter. The NGV stock fraction is similar in that it is primarily sensitive to the NGV cost, but at low values of high efficiency cost there is an increase in NGV adoption. These trends together create an interesting NGV high efficiency adoption pattern that appears generally symmetric across the two parameters.

The diesel high efficiency stock fraction figure illustrates that inexpensive NGV cost minimally decreases diesel high efficiency stock indicating a small amount of competition between NGVs and high efficiency diesels. However, as the total high efficiency stock fraction figure illustrates, the NG high efficiency vehicles more than compensate for the decline in diesel high efficiency vehicles. Further, contrary to a technology competition view, low high efficiency cost actually increases the NGV stock fraction.

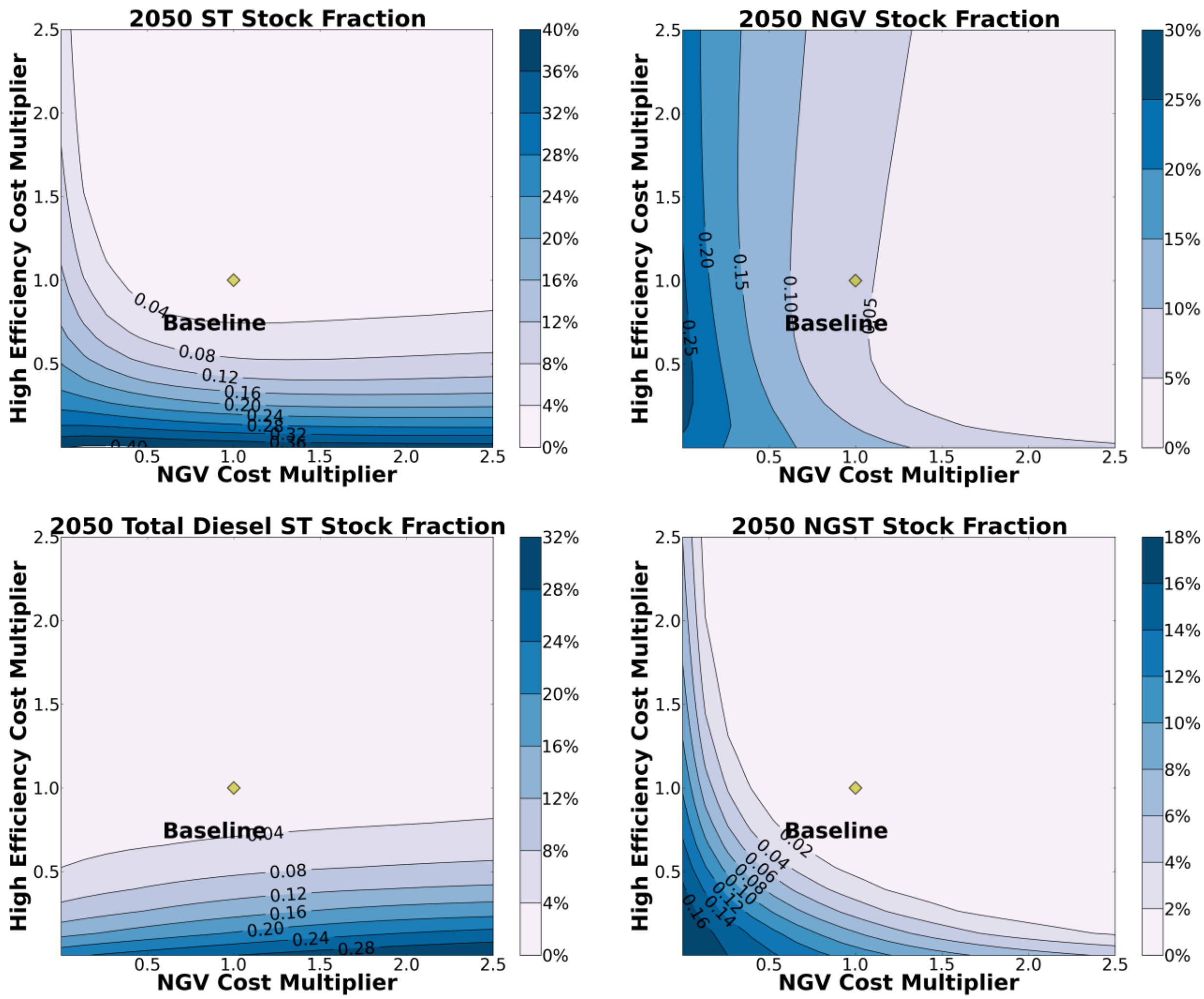


Figure 42: 2050 high efficiency vehicle and natural gas stock fractions by high efficiency cost multiplier and NGV incremental cost multiplier.

As shown in Figure 43, both diesel consumption and GHGs are minimized when both high efficiency cost and NGV cost are minimized. However, NGV cost is influential in reducing diesel consumption over the full range, whereas NGV cost is only influential over the low end of the parameter range (i.e., where the high efficiency NGVs penetrate the market) for GHG emissions.

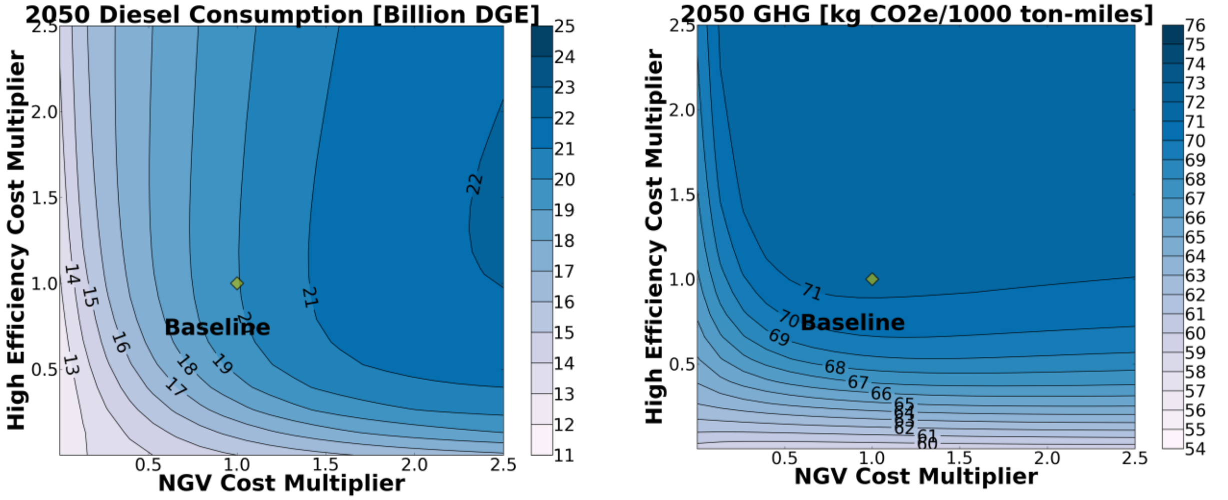


Figure 43: 2050 diesel fuel consumption and GHG emissions by high efficiency cost multiplier and NGV incremental cost multiplier.

Some competition between NGV technologies and high efficiency technologies is present, but the more significant trend appears to be not whether a low cost option for either high efficiency technologies or NGVs prevents the adoption for the other, but where combinations of costs appear to encourage the adoption of high efficiency NGVs.

3.4.3 Analysis of the market for natural gas vehicles

The NGV efficiency multiplier investigates the significance of the lower NG engine efficiency as compared to diesel engines. This multiplier is varied between -1 to 1 and is applied to the difference between diesel efficiency (Deff) and natural gas efficiency (NGeff) to create a scaled natural gas efficiency value ($NGeff_{scaled}$) as follows.

$$NGeff_{scaled} = multiplier*(Deff-NGeff)+NGeff$$

As Figure 44 illustrates, increasing NGV efficiency generally increases the number of NGVs as they become more attractive as fuel costs decline. Similarly decreasing NGV costs also increase NGV adoption as the initial purchase premium declines. For any set NGV cost, less than 2 percent increase in NGV adoption arises from increasing baseline NGV efficiency to diesel efficiency, potentially indicating that the efficiency differential between spark and combustion ignition engines is not a driving factor in precluding widespread NGV adoption.

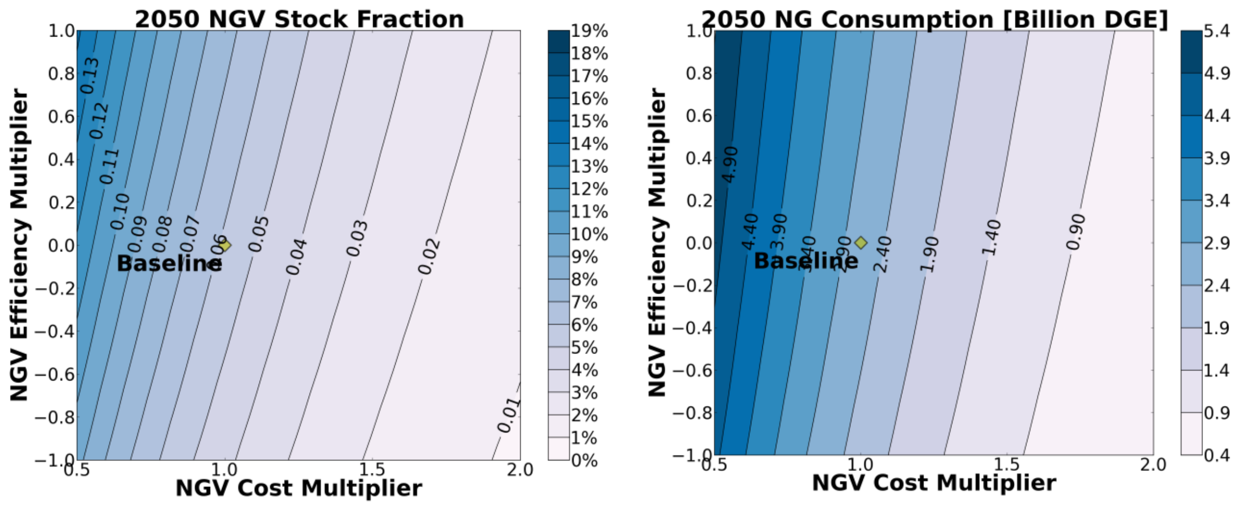


Figure 44: 2050 NGV stock fraction and natural gas consumption by NGV cost and efficiency.

Figure 45 shows the influence of the inexpensive, high efficiency NGV availability on diesel consumption and GHG. The more diesel vehicles converted to natural gas, the less total diesel consumed. GHG emissions, however, influenced both by the total number of NGVs as well as their efficiency. Over the parameter space shown, little influence on GHG emissions is evident due to the carbon intensity of NG fuel and the limited range of NGV efficiencies.

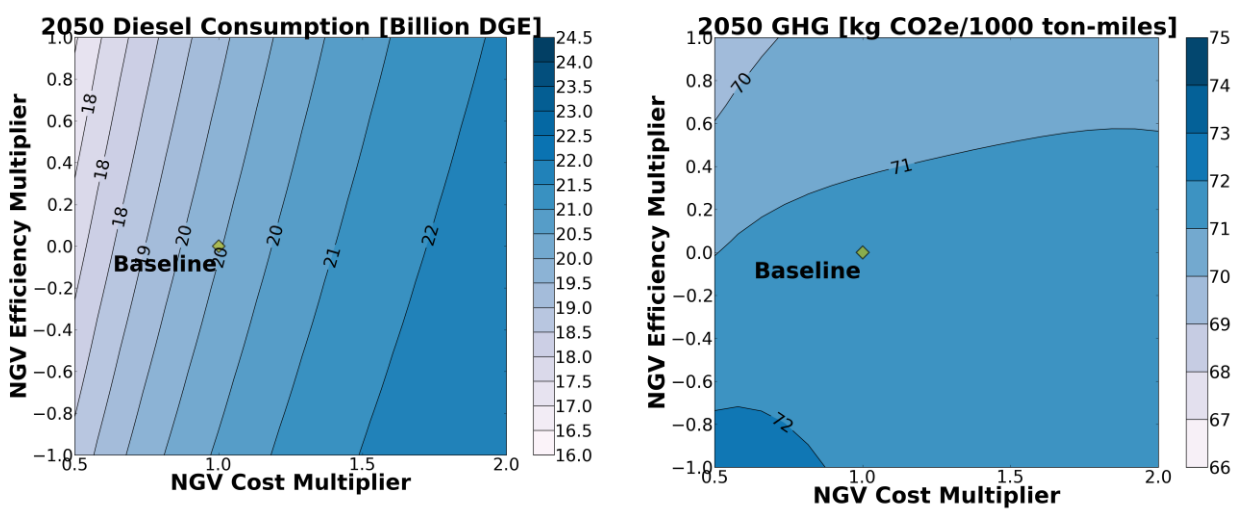


Figure 45: 2050 diesel consumption and GHG emissions by NGV cost and efficiency.

The market for standard and high efficiency NGVs also depends on the vehicle purchaser payment period as this dictates how quickly any initial cost must be recouped. Figure 46 shows that at long mean payment periods (value that scales both large and small fleet payment periods), NGVs comprise over 20 percent of the total vehicle stock and high efficiency NGVs reach over 8 percent of total vehicle stock at baseline cost values. However, if vehicle purchasers are willing to accept longer payment periods and NGV prices decline, NGVs could grow to over a third of the HDV stock with high efficiency versions also widely adopted.

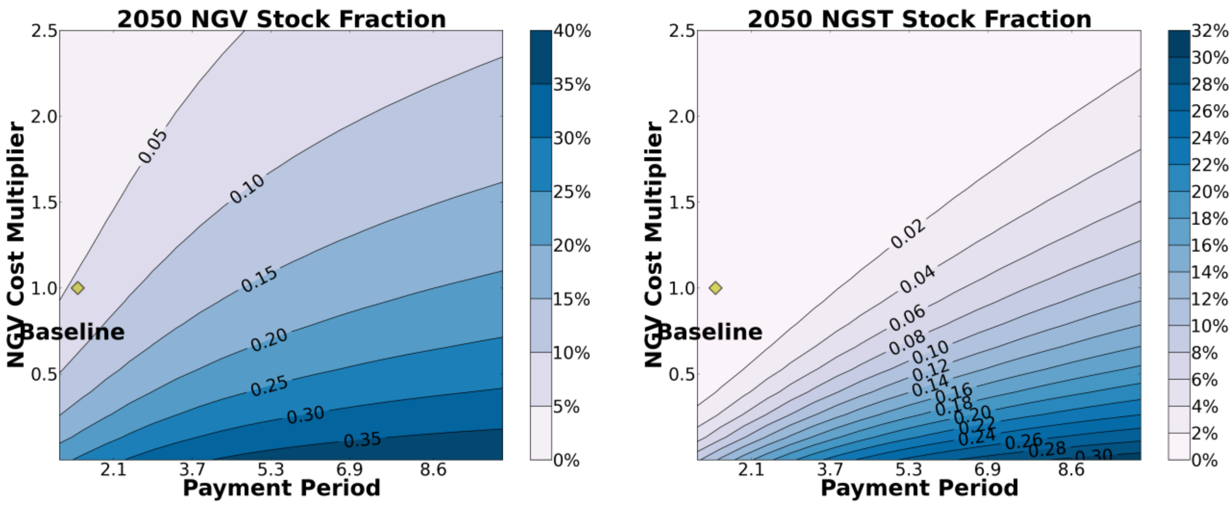


Figure 46: 2050 natural gas and high efficiency natural gas stock fractions by payment period and NGV cost.

As shown in Figure 47, LNG adoption is relatively insensitive to payment period while CNG adoption is sensitive to both initial cost and payment period.

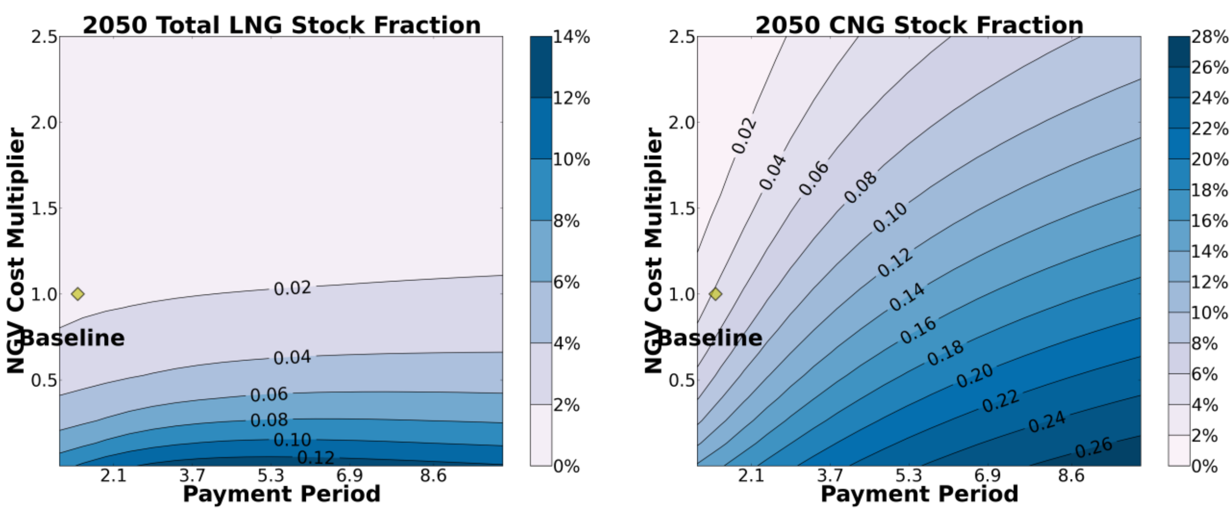


Figure 47: 2050 NG stock fractions by payment period and NGV cost.

As shown in Figure 48, significant diesel consumption and GHG reductions are achieved by the combination of low NGV cost and longer payment period. Some of this savings is due to the adoption of high efficiency vehicles in addition to the NGV adoption as the payment period increases.

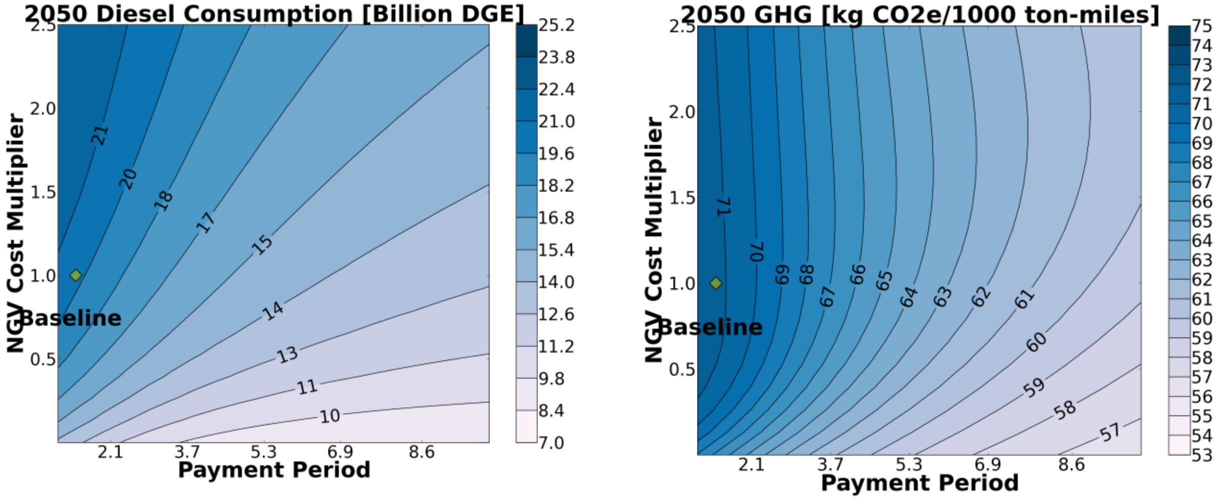


Figure 48: 2050 diesel consumption and GHG emissions by payment period and NGV cost.

At baseline values, there is low penetration of NGVs in the HDV sector in 2050. This adoption of NGVs can be increased through encouraging longer payment period acceptability to vehicle purchasers but reduced initial cost or increased efficiency could more strongly push the adoption of NGVs. An increased fraction of NGVs, however, contributes more toward reducing diesel consumption than toward meeting GHG emissions reduction goals.

3.4.4 Analysis of the market for high efficiency vehicle technologies

The market for high efficiency technologies is also investigated. Figure 49 shows high efficiency stock fractions of up to 48 percent for very high efficiency and very low cost technology options. Diesel high efficiency vehicles comprise the majority of these vehicles. In order for significant adoption to occur, high efficiency technologies need to be less expensive than their baseline values. Increased efficiency performance will also increase adoption though to a less significant degree.

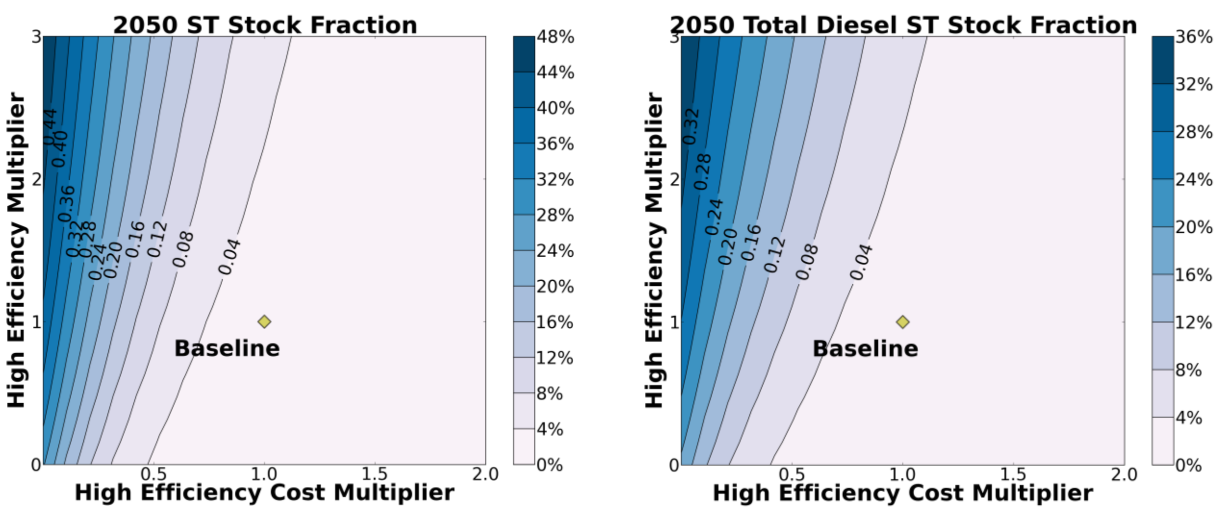


Figure 49: 2050 high efficiency stock fraction and diesel high efficiency stock fraction by high efficiency vehicle cost and efficiency.

Comparison of Figure 49 with Figure 50 shows that in order for NGVs to adopt high efficiency technologies, the costs need to be lower than for diesel vehicles, which follows from the respective potential fuel savings. Because of the lower upfront cost of the CNG vehicles as compared to LNG vehicles, more high efficiency technology penetration for CNG vehicles is seen across this parameter space.

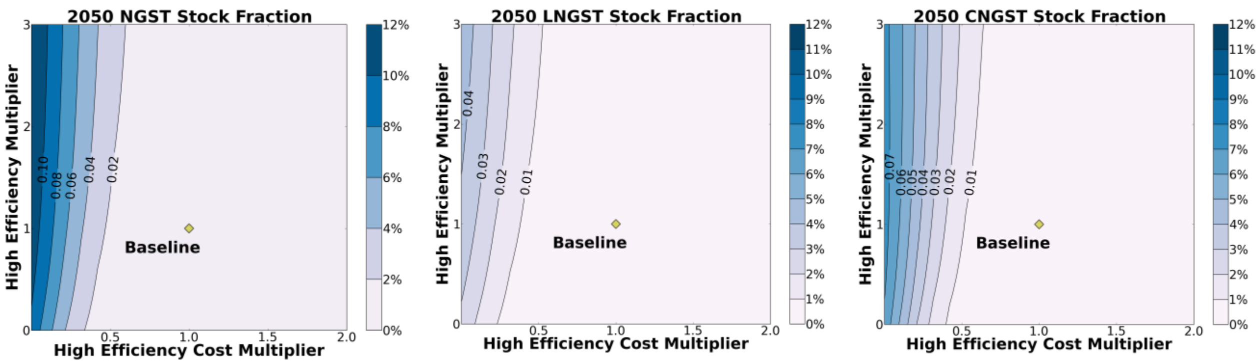


Figure 50: 2050 natural gas high efficiency stock fractions by high efficiency vehicle cost and efficiency.

Figure 51 shows that the relationship between these parameters and diesel consumption is complicated by the interplay between high efficiency technology adoption and NGV adoption. For example, the small peak in diesel consumption occurring at a low value of high efficiency multiplier near baseline high efficiency cost is driven by the competition between standard diesel, high efficiency diesel, and various natural gas powertrains as shown in Figure 52. GHG emissions monotonically decrease from low efficiency-high cost to high efficiency-low cost because the adoption of both natural gas and high efficiency technologies drives down GHG emissions and the slight rebound in the number of NGVs toward the high end of the high efficiency cost is insufficient to compensate for the substantial decline in high efficiency adoption across both diesel and natural gas powertrains.

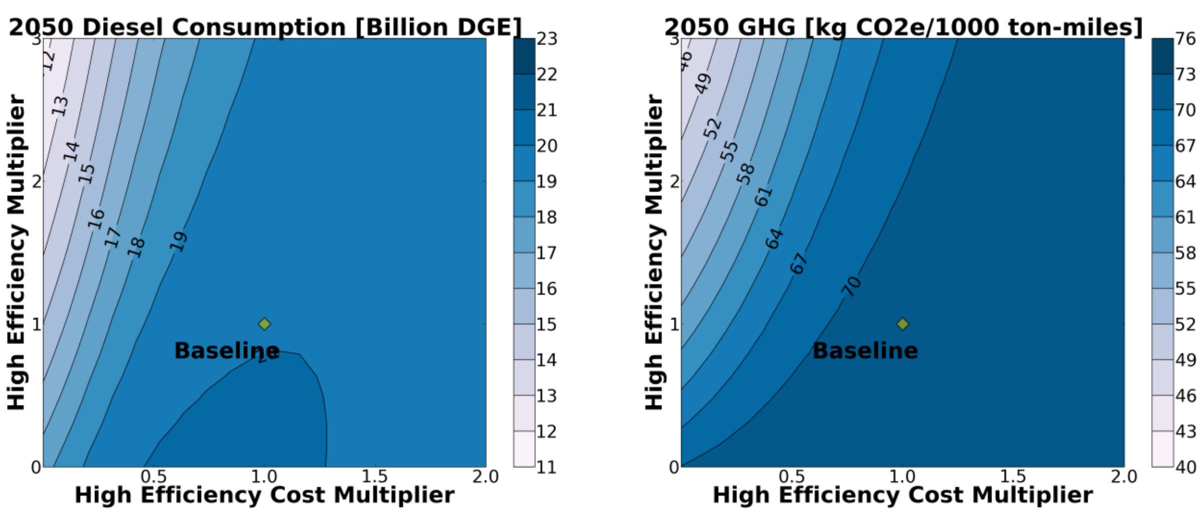


Figure 51: 2050 diesel consumption and natural gas consumption by high efficiency vehicle cost and efficiency.

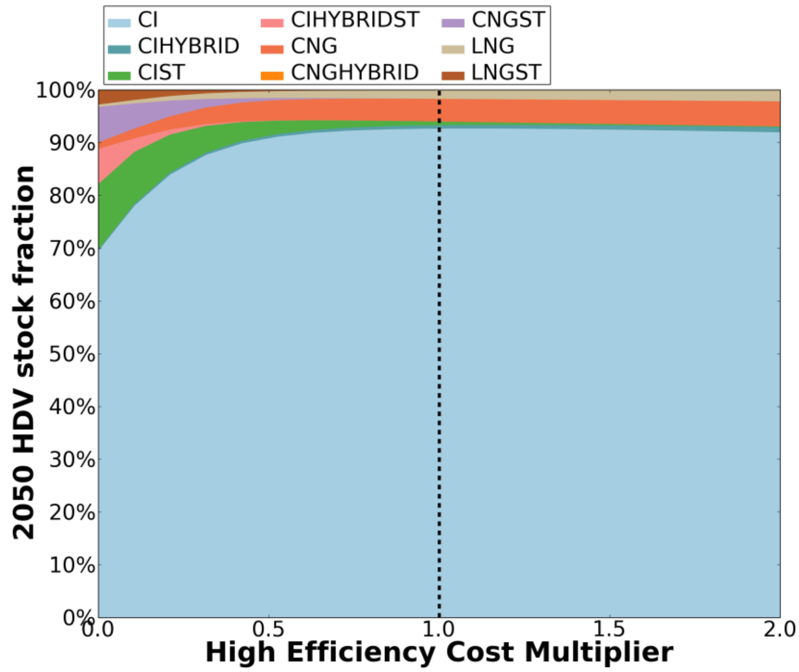


Figure 52: 2050 HDV stock fraction by high efficiency cost multiplier at high efficiency multiplier equal to 0.

As with the purchase of NGVs, payment period is a significant factor in the purchase of high efficiency technologies because the longer the acceptable payment period for the purchaser, the longer the cumulative operating cost savings can take to pay off high initial costs. Figure 53 shows that the total 2050 diesel stock fraction varies with payment period but is relatively insensitive to the high efficiency technology cost except at very low costs.

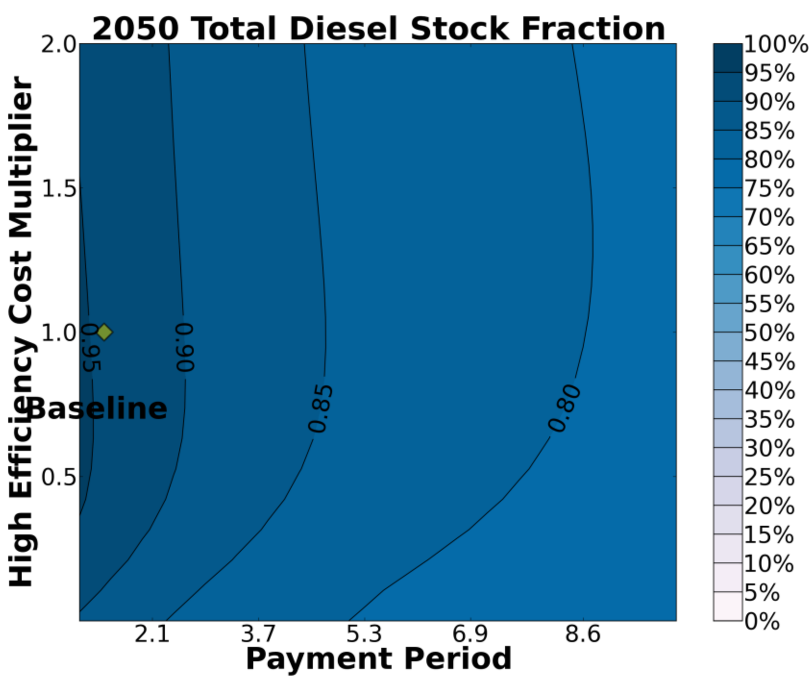


Figure 53: 2050 diesel stock fraction by payment period and high efficiency vehicle cost.

Figure 54 shows the high efficiency powertrain stock fractions for diesel, LNG, and CNG vehicles. While adoption of high efficiency technologies is sensitive to both high efficiency cost and payment period, the LNG high efficiency stock fraction remains very small across the parameter space.

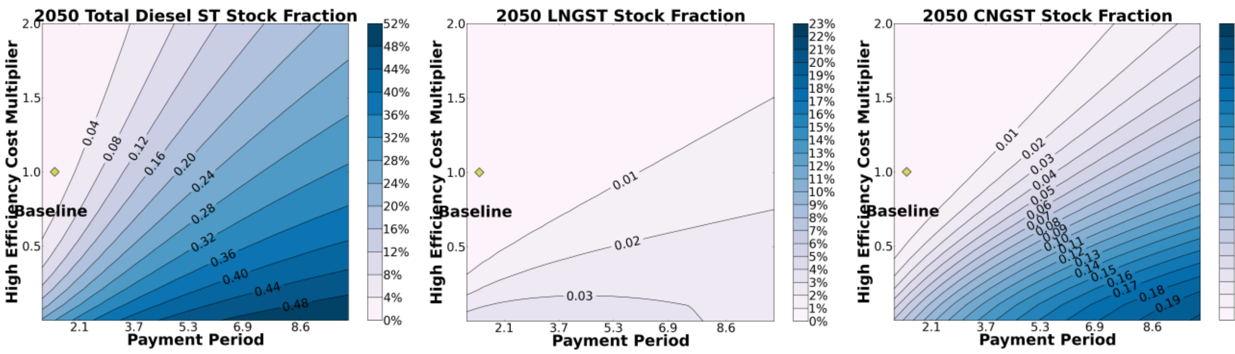


Figure 54: 2050 LNG stock fractions by payment period and high efficiency vehicle cost.

Figure 55 shows how these two parameters together influence diesel consumption and GHG emissions. Both diesel consumption and GHG emissions decrease with cheaper high efficiency technology as well as longer payment periods due to the influx of NGVs and high efficiency vehicles.

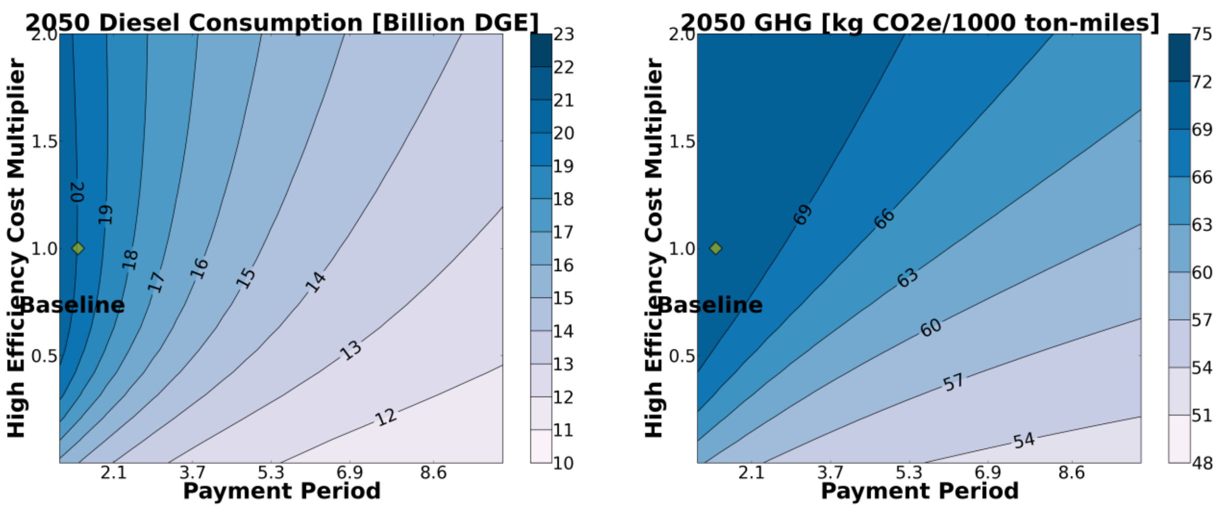


Figure 55: 2050 diesel consumption and GHG emissions by payment period and high efficiency vehicle cost.

While in the baseline case limited adoption of high efficiency technologies occurs, there is potential for more widespread adoption of these technologies if they can be made cheaper or more efficient or if vehicle purchasers are willing to accept longer payment periods.

4 CONCLUSIONS AND FUTURE EXTENSIONS

This model can be used in several ways to address a variety of questions for different stakeholders. To address energy security concerns, the model indicates how parameters impact total fuel and diesel consumption. For answering questions about climate change and the environment, the model can be used to identify the major drivers behind GHG and other emissions. The model also considers the demand for natural gas and alternative powertrains for stakeholders interested in the potential market for natural gas as an HDV fuel, NGVs, and hybrid or high efficiency technologies. Table 3 shows that the parameters the output metrics are most sensitive to vary, so levers to influence the outputs may be goal-specific.

Table 3: Output metrics and the top three parameters to which each is sensitive.

Output metric of interest (direction of potential intended outcome)	Top three parameters to which the output is sensitive (direction parameter drives the output)
Fuel/Ton-mile (-)	1. ICE Efficiency (-) 2. High Efficiency Cost (+) 3. Hybrid/High Efficiency (-)
Diesel/Ton-mile (-)	1. ICE Efficiency (-) 2. Oil Price (-) 3. Natural Gas Price (+)
GHG Emissions (-)	1. ICE Efficiency (-) 2. High Efficiency Cost (+) 3. Hybrid/High Efficiency (-)
Hybrid Vehicle Adoption (+)	1. Hybrid Efficiency (+) 2. Hybrid Cost (-) 3. Large Fleet Payment Period (+)
High Efficiency Vehicle Adoption (+)	1. High Efficiency Cost (-) 2. Large Fleet Payment Period (+) 3. High Efficiency (+)
Natural Gas Vehicles Total (+)	1. Oil Price (+) 2. Natural Gas Price (-) 3. Infrastructure Cost Factor (-)
Compressed Natural Gas Vehicles (+)	1. Oil Price (+) 2. Natural Gas Price (-) 3. Infrastructure Cost Factor (-)
Liquefied Natural Gas Vehicles (+)	1. Natural Gas Price (-) 2. Oil Price (+) 3. Infrastructure Cost Factor (-)

Reducing fuel use, diesel use, and are all most sensitive to the underlying internal combustion engine efficiency which makes sense as this parameter influences the efficiency of all trucks within the model. However, while diesel consumption is subsequently most sensitive to fuel prices (which influence the NGV adoption), reducing total fuel use and therefore GHG emissions is more sensitive to the parameters that influence adoption of additional efficiency technologies (i.e., their respective costs and efficiencies).

While high oil prices and low natural gas prices shift trucks from diesel to natural gas, because both diesel and natural gas are carbon intensive fuels this shifting does not have a comparable impact on GHG emissions as on diesel consumption. Thus, achieving diesel consumption and GHG emissions reduction goals may be achieved through different mechanisms.

One policy option that may be used to influence diesel consumption is raising the cost of diesel through increased taxes. Figure 56 shows the potential influence of varying diesel taxes. The dark dashed line represents the baseline oil price, the yellow dashed line represents a 10 percent decrease in oil price from baseline (equivalent to a tax reduction), and each pink dashed line indicates an additional 10 price increase (equivalent to tax increases). The top plots how these lines across natural gas price as well and the lower plots show a projection of this space along the baseline natural gas price. If the 2050 fuel prices are near the baseline value, it would require tax increase of 25 percent to reduce diesel consumption 10 percent. This same tax increase would cause a less than half of a percent GHG emissions reduction. The plots on the top indicate that increasing natural gas price would slightly increase the impact of increased taxes. However as oil price increases tax rates must also increase to maintain impact in both absolute and fractional reductions.

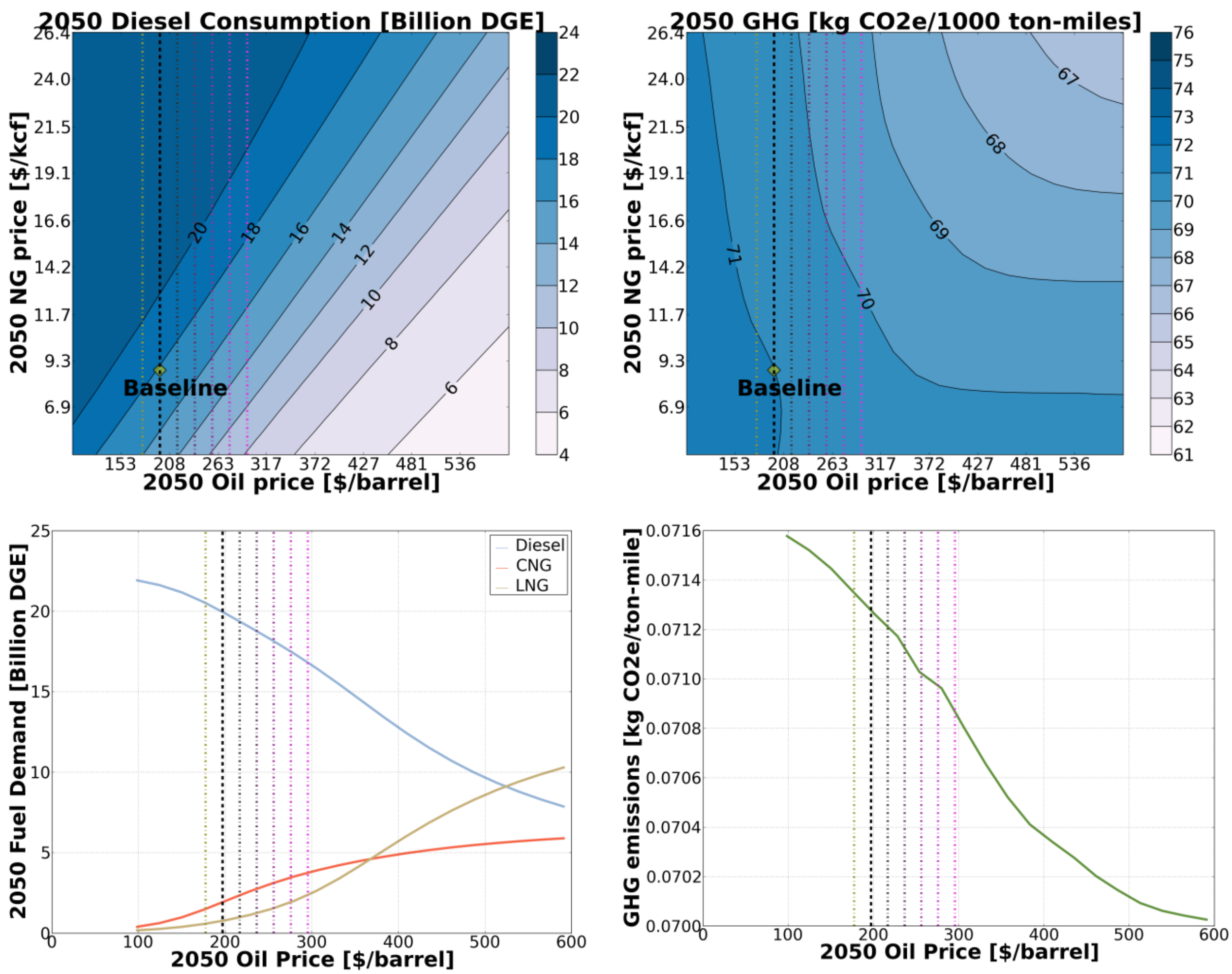


Figure 56: Influence of diesel fuel taxes on diesel consumption and GHG per ton-mile.

While this model can be used to provide valuable insights into the future of HDVs and broader implications, the precision and specificity of the results is limited by the relative lack of data availability for the HDV sector as compared to the LDV sector. This model will be significantly improved as more data is collected and made available, including updated, detailed information about the HDV stock and its segmentation. Refined future cost projections across powertrains will also enable a more precise analysis. Additionally, a more detailed understanding of how HDV purchasing decisions are made and how they vary across fleet size and other factors could be used to further improve the model. This would include understanding how pilot fleets are initiated and expanded among large owners and how these pilot fleets influence purchasing behavior beyond the initial owner. It would also include understanding how risk and uncertainty are viewed by vehicle purchasers.

This model can be adapted to address several interesting HDV-related questions that were considered out of scope during the initial model development. The current model considers categories of technological alternatives, but individual technologies with specific cost, performance, and availability timeline parameters could be added to assess alternatives at a more detailed level. As other powertrains become commercially available for certain categories of HDVs, these could also be added to the model to identify their prospective impact. Additionally, the initial model considers only initial vehicle configuration and owner, but HDVs often have multiple lives. Incorporating the resale market and after-market conversions could provide interesting insights into how these important and somewhat unique aspects of the HDV sector encourage or inhibit achieving diesel consumption and emissions goals.

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